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Improving College Students' Self-knowledge Through Engagement in a Learning Frameworks Course

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Improving College Students' Self-knowledge Through Engagement in a Learning Frameworks Course

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Dedication

To Mom and Dad, with love

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Or, where I attempt to express in words the overwhelming gratitude that fills my heart

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Improving College Students' Self-knowledge Through Engagement in a Learning Frameworks Course

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This study tested hypotheses about the accuracy of students' strategic learning self-assessments using a sample of students enrolled in an undergraduate learning frameworks course at a highly competitive research institution. Previous studies demonstrated that learning frameworks courses significantly improve grade point averages, semester-to-semester retention rates, and graduate rates (Weinstein et al., 1997; Weinstein, 1994). Less is known, however, about changes that happen during the semester. Researchers have found that students tend to overestimate their academic abilities (Miller & Geraci, 2011), but that improving participant skill levels increases their ability to recognize the limitations of their abilities (Kruger & Dunning, 2009). This study built on the existing learning frameworks and calibration literatures and addressed the following research questions: Does students' calibration accuracy improve from the beginning to the end of a semester-long strategic learning course (a type of learning frameworks course)? Does generation status influence calibration? What is the relationship between an individual's theory of intelligence and their strategic learning calibration? And, is there a relationship between accurate self-assessment and demographic factors such as family income and ethnicity?

The methods used in this study included self and objective assessments of strategic learning for 10 learning factors known to impact student success. Based on the Model of Strategic Learning (Weinstein, Acee, Jung, & Dearman, 2009), these 10 factors were assessed by the Learning and Study Strategies Inventory, 2nd Edition (LASSI) (Weinstein & Palmer, 2002). The 10 LASSI scales are: Anxiety, Attitude, Concentration, Information Processing, Motivation, Study Aids, Self Testing, Selecting Main Ideas, Test Taking, and Time Management. Each scale has 8 items (80 total) and uses a 5-point scale ranging from 1 (almost never true of me) to 5 (almost always true of me). Measurements took place at two time points: beginning and end of the semester. The sample size was 507 university students in one of 22 sections of a lower division educational psychology learning frameworks course. Initially students were given brief oral descriptions of the 10 scales and asked to rate their strengths in each area on a 100-point scale to assess their perceived level of strategic learning. Students then completed the 10-scale LASSI instrument, received feedback on their strategic learning level for each scale, and reflected on the discrepancies between self-assessed (predicted) scores and actual scores. I used mixed ANOVA and regression analyses to identify how accurate students were at the beginning of the semester, how accurate they were at the end of the semester, if this difference was significant, and if other factors – a student's theory of intelligence, parental education level, family income, and ethnicity – were related to the accuracy of these self assessments. I was particularly interested in the extent to which the least strategic students became more accurate in their self-assessments.

Overall, three key findings emerged from the current study: 1) Students' initial self-assessments were inaccurate and, for the most part, students overestimated their actual strategic learning capabilities, 2) self-assessments are amenable to change and accuracy can improve within a learning frameworks course, even among the least strategic learners in this sample, and 3) parental education level was associated with actual level of strategic learning for some factors at the beginning of the semester, but by the end of the semester, it was no longer a significant predictor. The relationship between the accuracy of student's self assessments and selected personal demographic factors (income and ethnicity) and their theory of intelligence were mixed.

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Chapter One: Introduction

U.S. colleges and universities enroll over 21 million undergraduate students each year, including more than 3 million first-time degree-seeking students (Snyder & Dillow, 2013). Although the national college-going rate increased from 54% to 62% between 1992 and 2006, college completion rates remained relatively flat with only 58% of first-time college students seeking a bachelor's degree graduating within 6 years (Kena et al., 2014). Persistence and completion rates for the over 4.5 million students who are the first in their family to go to college are even lower (Engle & Tinto, 2008). These first-generation students are twice as likely to drop out of college compared to their continuing generation peers (Chen & Carroll, 2005). With a charge to postsecondary institutions from federal, state, and local sources to increase persistence and completion rates, institutions are implementing a multitude of promising practices in an effort to help students succeed academically, including enrolling academically vulnerable students in courses designed to help them become strategic learners, what I call in this document *learning frameworks courses*.

Offered with the hope of bolstering students' academic performance, learning frameworks courses have as their overall aim to help students become self-regulated strategic learners who actively take responsibility for their learning and use appropriate learning strategies to achieve their academic goals (Donker, de Boer, Kostons, Dignath van Ewijk, & van der Werf, 2014). To achieve these ends, students engage in both the study and the application of theories of cognition, motivation, and self-regulation, elements known to impact learning (Hodges, Dochen, & Sellers, 2001; Weinstein, Acee, Jung, & Dearman, 2009; Weinstein & Mayer, 1986). The hope is that as students study theories of cognition, memory, motivation, and self-regulation, they will develop a personalized toolbox of strategies useful in helping them navigate their academic (and personal) environments and leverage knowledge about how students learn to achieve greater academic success. Learning frameworks courses demystify and normalize the learning process and provide a space for students to try out learning strategies and get feedback on how well they worked. Researchers have found that students feel that these courses help them succeed in college and have demonstrated that learning frameworks courses significantly increase grade point averages, semester-to-semester retention, and graduation rates (Weinstein et al., 1997;Weinstein, 1994).

Statement of the problem

Although learning framework courses can help students achieve greater academic success, some students who take such courses do not have positive outcomes. And even for courses with a general history of success, little is known about which components of the course drive the positive future outcomes. Of particular interest in this study is whether students in a learning frameworks course are developing a more accurate understanding of themselves as learners. This is especially important for first-generation college students who can benefit from interventions aimed at increasing knowledge of what it takes to be strategic learners in college. Having an accurate understanding of themselves as learners is an essential element in becoming self-regulated learners. Therefore, it is important to understand if students' perceptions of their strategic learning ability are accurate and whether these perceptions change as a result of taking a semester-long course engaging in content from the learning, motivational, and cognitive sciences.

First-generation college students

First-generation college students are the first in their family to attend college. They disproportionately come from lower income families and are more likely to identify as belonging to one or more ethnic minority groups (Nunez, 1998; Terenzini, Springer, Yaeger, Pascarella, & Nora, 1996). Additionally, low-income first-generation students tend to be older, female, are less likely to receive financial support from parents, and more likely to have multiple obligations outside college, such as family and work, that limit their full participation in the college experience (Engle & Tinto, 2008).

Researchers have found higher first-year dropout rates among first-generation students when compared to non-first-generation students, as well as less persistence toward a degree in both two-year and four-year institutions (Berkner, Horn, Clune, & Carroll, 2000; Billson & Terry, 1982). In a longitudinal study focused on first-generation student attrition, Ishitani (2003) found that the risk of attrition in the first year among first-generation students was 71% higher than that of students with two college-educated parents. Even when first-generation students are enrolled in college, they tend to earn lower grades and complete fewer credit hours.

Explanations for these differential outcomes have focused on two broad categories: high school preparation and social capital differences. Some researchers cite the lack of rigor in first-generation students' high school coursework and their lack of engagement with peers and teachers in high school as the root of the persistence and completion differences (Bromberg & Theokas, 2014; Chen & Carroll, 2005; Pascarella, Pierson, Wolniak, & Terenzini, 2004).

Other explanations for poor first-generation student outcomes focus on differences in their social capital. Continuing-generation students have access to important information about how to do college by virtue of life-long access to parents who have had those college experiences. Parents of continuing-generation students may disclose important information about what it takes to be successful in college (e.g., time management, the bureaucratic operations of higher education, the culture of higher education). Therefore, their children have many opportunities prior to starting college to develop appropriate approaches for handling the expectations and tasks in college, including dealing with teachers and peers. This gives continuing-generation students an advantage over students whose parents do not have similar experiences to share. At the same time, first-generation students who have made it to a top-tier university may embody characteristics that enable them to do high quality work required for admission and it may be the case that these students have acquired the college know-how from sources other than their parents.

This study takes place at the college level, and therefore cannot rectify differences in rigor at the high school level or previous interactions with parents, peers, and teachers. It does, however, provide an opportunity to look closely at the accuracy of first-generation students' self-knowledge and what it means to be a strategic learner. Increasing this kind of knowledge should help lessen the information disparity about one aspect of the college experience for first-generation students and improve their academic outcomes.

Theoretical frameworks

This study depends heavily on Bandura's (1986; 1989; 2001) social cognitive theory as a theoretical framework. In this theory, Bandura defined human behavior in terms of continuous, dynamic, reciprocal interactions between cognitive, behavioral, and environmental influences and advanced the notion that individuals are proactive, engaged agents who can make things happen by their actions. These actions are influenced by individuals' self-beliefs and how they interpret their own prior thoughts, feelings and behaviors (Bandura, 1986).

The Model of Strategic Learning (MSL) also serves as a theoretical framework for this study (Weinstein, Tomberlin, Julie, & Kim, 2004). The MSL itself subsumes numerous theoretical constructs and was an explicit basis for the content of the learning frameworks course used in this study as an organizing structure for readings, assignments, and for classroom discussions. The MSL organizes factors known to influence learning in a holistic way, recognizing that the interactions among individual and environmental factors represented in the model have greater impact on student success than any one factor alone.

In the MSL, factors that impact learning are called *elements* and are organized under four components: skill, will, self-regulation, and the academic environment. Elements in the skill, will, and self-regulation components are central to this study. The skill component includes knowledge factors (such as a learner's knowledge about himself/herself as a learner and knowledge about the learning context) and skill in using study strategies and skills. The will component captures students' beliefs, attitude, emotions, and motivation, all factors that impact a student's desire to use knowledge and skills to be successful in college. One belief that has gained much recent attention in the educational research literature as a critical element in student success is a student's belief about how intelligence works, specifically, about whether intelligence is a fixed quantity or whether, with effort, intelligence can change and grow.

The self-regulation component includes active, purposeful behaviors in which a student engages to manage skill and will factors. Within the past two decades, self-regulation research has expanded our understanding of how students plan, monitor, and exert control over their thoughts and actions and how students' knowledge and beliefs can influence the process. Calibration incorporates knowledge of self as a learner and beliefs about one's capabilities, and is a necessary element in the self-regulation (Winne, 2004) that drives forward effective self-regulated learning cycles of planning, monitoring, and evaluating (Nietfeld & Schraw, 2002). I review the research on calibration in the next section.

Calibration

Calibration is the process of creating an internal assessment of performance and comparing it against a standard for performance (Nietfeld, Cao, & Osborne, 2006; Winne, 2004). Measured as the difference between an individual's predicted and actual performance (Bol, Hacker, O'Shea, & Allen, 2005; Lin & Zabrucky, 1998), calibration can be divided into two factors: accuracy and bias. Calibration accuracy is the absolute difference between predicted performance and actual performance. Bias measures the direction of that deviation. If an individual's predicted performance is greater than the actual performance, the individual is positively biased, or overestimating performance. On the other hand, when actual performance exceeds predicted performance, the individual is said to be negatively biased, or underestimating performance. As the difference between perception and actual performance decreases, calibration improves (Nietfeld et al., 2006).

A learner's accurate understanding of himself/herself as a learner and of the task requirements can influence how the student plans to allocate study resources (time, materials) and which study strategies to select for the tasks at hand. Accurate monitoring influences whether or not a student decides to persist and if he/she persists by continuing to implement the original plan or by adjusting effort or strategies in response to new information. Indeed, students with more accurate assessments of themselves tend to allocate study time more efficiently and have better academic outcomes (Marsh, Trautwein, Ludtke, Koller, & Baumert, 2005). However, a long line of research demonstrates that, in general, self-assessments are inaccurate.

Self-assessment inaccuracies are most often positively biased; that is, individuals tend to overestimate their reasoning abilities (Kruger & Dunning, 1999), knowledge of facts (Lundeberg, Fox, Brown, & Elbedour, 2000), and their academic abilities (Miller & Geraci, 2011). In one study of exam performance calibration, Hacker, Bol, Horgan, and Rakow (2000) found that many undergraduate students predicted they would earn exam scores that were more than 30% higher than their actual scores. Correcting these inaccuracies could help all students be successful, but would be particularly useful for students who often struggle academically and lack parental guidance to help them assess how "on track" they are. In general, high achievers are more accurate in their predictions than are low achievers (Bol et al., 2005; Dunning, Heath, & Suls, 2004; Hacker et al., 2000). The leading interpretation for this finding is that low performers are more overconfident because they lack metacognitive insight; in addition to not having content knowledge, they are unaware that they lack this knowledge. Although some amount of overconfidence could be useful as a protective mechanism, leading students to persist when faced with small challenges, the large distortions seen with low performing students could lead to incredibly poor study-related decision-making because it is based on incomplete or erroneous information.

Low performers' consistent overconfidence may be more complicated than just a lack of metacognition, however. First-generation students may be using incorrect standards in their self-assessments. Most calibration research focuses on individuals monitoring their performance relative to a standard of achievement within a specific content domain (e.g., writing, mathematics). Calibration researchers have studied students' evaluations of how easy or difficult it will be to meet the standards of a simple task, how confident students are that they correctly answered a question on an assessment they just took, and whether or not they would be able to answer questions about a topic correctly on a future assessment (Winne, 2004). In some studies, students are asked to assess their performance on a specific item on its own, and sometimes students are asked to make a relative comparison of confidence between multiple items. Consistent in all studies, however, is that there is always a standard against which study participants evaluate their own performance.

Standards play an important role in calibration because they provide information against which a self-perception is evaluated. Knowledge of the standards for performance in college is derived from personal and vicarious experiences. As they begin college, neither continuing generation nor first-generation students have personal experiences of college, but continuing generation students have had the opportunity vicariously to acquire knowledge of college standards and expectations through conversation with family members about their own college days. As first-generation and continuing-generation students persist through college, they continue to have differential access to experienced family members who can provide guidance about navigating through the mundane and challenging aspects of higher education. Festinger (1954) proposed that when objective standards are lacking, individuals assess their abilities and opinions by comparing themselves with similar others. And, even when standards are available, individuals across their lifespan gravitate toward making social comparisons when assessing their abilities (Suls, Marco, & Tobin, 1991). Therefore, in the absence of this vicariously acquired knowledge, first-generation students could substitute these standards with comparisons that will lead them to make calibration assessments that are biased or inaccurate. Calibration can be improved, however, by correcting incomplete or inaccurate information (Winne, 2004). Learning frameworks courses help students build knowledge of the environmental, personal, and behavioral elements that influence learning in college courses, filling in missing information and correcting erroneous assumptions that first-generation students may have about how learning works.

Calibration necessitates that students continually reflect on their past performance and update their beliefs about themselves and what they know. It follows that their beliefs about whether or not their intelligence can change will influence this process. Students who believe that, with effort, they can earn higher grades and improve their academic standing are said to have a "malleable" sense of intelligence, a *growth mindset* (Dweck, Chiu, & Hong, 1995). These students may have a more accurate understanding of their knowledge level, as they are open to the idea that their intelligence will change and may, therefore, spend time engaged in reflection. Students who believe that their intelligence level is *fixed*, on the other hand, could disengage from considering their own actions (e.g., studying for an exam) and thus be unaware of their true level of knowledge.

Significance of current study

At a high level, this study sheds light on the accuracy of students' perceptions of themselves as strategic learners. In studying calibration within an authentic context, this work adds to the small number of studies conducted outside of lab settings (Hacker et al., 2000). The course used in this study focuses on calibration of strategic learning in general - not with respect to a specific content area and strategies customized to those environments. Whereas other calibration research is embedded within a specific domain (reading comprehension in an English class, statistics problem solving), this study took place in a course designed to help students become self-regulating agents in all content areas. As an aspect of self-regulation, calibration is influenced by many factors. No empirical evidence establishing the relationship between calibration accuracy, generational status, and intelligence beliefs exists.

In this study, I explored whether a course devoted to helping college students become self-regulating, strategic learners would influence the accuracy of students' self-knowledge. Participants in this study were enrolled in an elective strategic learning course at a competitive research institution. Reasons for enrollment in the course vary, but academic advisors frequently recommend enrollment to students who are at risk for negative academic outcomes or who have already performed poorly at the university. I tested the hypotheses that initially students' calibration of their strategic learning abilities is poor and that changes over time differ based on initial strategic learning scores. Further, I tested the hypothesis that first-generation students' calibration improves from the beginning to the end of the semester and that students endorsing a growth mindset are more likely than their fixed mindset peers to (a) be more accurate in their perceptions of strategic learning ability at the beginning of the semester, and (b) demonstrate improved calibration across time, as they are more likely to incorporate prior feedback into their future calibration attempts. Understanding if perceptions of strategic learning ability change across a semester when taking a strategic learning course and whether students' beliefs about intelligence and their first-generation status make a difference in explaining what they learn from such a course can help educators and researchers refine learning frameworks courses in the future.

Chapter Two: Literature Review

Why focus on student success?

Enrollment in higher education is increasing each year, driven in part by societal beliefs that education is an essential element that influences future economic benefits and upward social mobility (Pike & Kuh, 2005). U.S. colleges and universities now enroll more than 21 million undergraduate students each year, including more than 3 million first-time degree-seeking students (Snyder & Dillow, 2013). Between 1990 and 2012, the percentage of high school graduates who immediately enrolled in college – either at a 4-year university or a 2-year college – increased from 60 to 66 percent (Kena et al., 2014). However, inequalities exist in who enrolls and who is successful. Some of these differences are driven by demographic characteristics (such as ethnicity and age), others by psychosocial elements (such as beliefs).

College completion rates have remained relatively flat with only 58% of first-time college students seeking a bachelor's degree graduating within 6 years (Kena et al., 2014). And, persistence and completion rates for the over 4.5 million students who are the first in their family to go to college are even more dismal (Engle & Tinto, 2008). First-generation students are twice as likely to drop out of college compared to their continuing generation peers (Chen & Carroll, 2005). These persistence and completion differences have garnered national attention, triggering demand for new and innovative approaches to help students adjust to and succeed in college. Highly competitive colleges and universities are not immune from these persistence and completion issues, and this study investigates the effectiveness of a student success intervention at a Tier 1 research university.

Interventions

Significant resources have been devoted to helping academically vulnerable students apply, enroll, and be successful in college. Colleges are increasingly investing financial and staff resources into mandatory orientation, intrusive advising, summer bridge, and learning community programs. Some of these programs help ease the transition from high school to college (e.g., bridge programs like Gear Up and TRIO and early college/dual credit programs in which students concurrently enroll in college and high school courses). Other programs concentrate on helping students find their way around campus by explaining registration and financial aid processes and connecting students with tutoring and advising services on campus. Learning communities, or a group of students who take two or more linked classes as a cohort, serve another purpose in promoting student success: providing extended time together across multiple settings to help students and faculty build a sense of community.

In general, these interventions are positively impacting student achievement and persistence. According to a recent Center for Community College Student Engagement report (2014), academically vulnerable students required to enroll in developmental education courses who report participating in an orientation program were 2.14 times more likely to complete a required developmental English course successfully and were 1.30 times more likely to complete a gatekeeper English course successfully. Even students without needs for additional developmental coursework benefit from these kinds of interventions. Non-developmental students who participated in an orientation program prior to starting class in the fall semester were 1.44 times more likely to enroll in college in the subsequent spring semester.

These promising results are a start at retaining students and helping them graduate, but there are important elements about becoming a successful learner that cannot be covered during these kinds of programs. Orientation and summer bridge programs, for example, are held prior to the start of classes before students have a chance to experience college life first hand. Students may not understand how valuable the information covered in these sessions will be to them until they actually attend their first college class and sit down to complete their first college assignment. Programs may simulate college life, but cannot recreate conditions in which students will actually need to navigate. Orientation programs have been shown to impact students' commitment to their institution and help them adjust to college, but have not been shown to have a significant effect on persistence (Pascarella and Terenzini, 2005; Kuh, 2006). One reason for this could be that students struggle to transfer what they have learned during orientation and other stand-alone programs to in-the-moment studying and learning during the semester. Students need to have all of their course syllabi in order to know how due dates overlap and to determine when to schedule study time. Students need to attend classes with their professors in order to assess the expectations of *these* instructors. And they need to experience the demands of college in order to evaluate their own habits and modify those behaviors that they discover are no longer serving them well in their new college environment. Course-based options provide just such an opportunity for extended study and practice developing the mindsets and strategies that are important for college success while the student is actively engaged in being a college student.

Course-based interventions

Course-based options date back to the late 19th century when Boston College offered an extended orientation seminar focused on helping students navigate the transition to college (Saunders & Romm, 2008). Over time, this course, and similar courses at other institutions, expanded to include social and personal development in addition to academic success. By the late 1930s, however, this form of student support began to fade, disappearing almost entirely by the 1960s (Saunders & Romm, 2008). A second wave of course-based interventions began in the late 20th century and, according to Barefoot and Fidler (1992), by 1991 most higher education institutions were offering some kind of extended orientation seminars (also referred to as college survival, college transition, or student success courses), discipline-linked seminars, or basic study skills courses as part of their first-year initiatives to support students.

Saunders and Romm (2008) credit this reemergence in course-based options to higher education institutions' open access policies that increased student enrollment. As enrollment increased, so did the diversity of experiences and level of preparation students brought with them. As some students struggled and other succeeded, faculty and administrators developed course-based interventions to help their students adjust to, stay in, and succeed in college. Institutions customized their course offerings to meet the needs of their own students and varied in how they incorporated the most recent research about how students learn and what helps them be successful in college. This led to a wide variation in the types of courses and the content discussed within each course, causing confusion in the field.

This variation and inconsistent labeling has also made it difficult to interpret the mixed findings on the effectiveness of these options. For example, some researchers have found that students enrolling in a success course in their first semester earned higher first-term grade point averages, completed more credits during their first term, were more likely to earn any college-level credits within their first year, were more likely to persist to the second year, and had greater odds of graduating (Cho & Karp, 2013; Glass & Garrett, 1995; Stovall, 2000). Other researchers conclude that success courses do not impact important outcome metrics such as graduation rates (Boudreau & Kromrey, 1994). But because the content and pedagogy used in these "success courses" is not consistent, it is difficult to draw general conclusions about the effectiveness of this kind of intervention.

To create a common understanding of the types and content of success courses, Cole, Babcock, Goetz, and Weinstein (1997) articulated specific categories of student success courses based on the content and theoretical underpinnings of the courses. This organization was later shared more widely by Hodges et al. (2001) and is used here to shape the following discussion of how success courses have evolved into the learning frameworks model used in this study.

Orientation and navigation courses are typically 1 or 2-credits meeting during the first-semester freshman year (Barefoot & Fidler, 1992; Cole et al., 1997). An extension of what might be covered in a brief one or two-day summer orientation session, some of these courses often cover many topics at a superficial level. Others focus on one of the topics more in depth, as the courses are tailored to meet the needs of the institution. Topics could include locating and identifying how and when to use campus resources, such as the library, academic and career advising, tutoring, and financial aid. These courses may also include a focus on making the transition from high school to college and living on one's own, career development, and life management (Stovall, 2000).

Study skills courses vary from 1 to 3 credits and focus on helping students acquire the habits and skills needed to find and use information in their academic studies (Hodges et al., 2001). Common topics within study skills courses include time management, note taking, working in study groups, and test taking. Despite consensus that these topics are incredibly important aspects of succeeding in college, courses that narrowly focus on presenting students with "ways to manage your time better," "common abbreviations to use when taking notes in class," or "how to take a multiple choice tests" face criticism.

One criticism of study skills courses is that students often struggle to apply the skills covered to other academic contexts (Karp & Stacey, 2013). For example, despite having discussed different ways to take notes, students struggle to do so effectively in their other courses. Karp and Stacey (2013) note that one reason for this outcome is that during the study skills course, students do not get a chance to try and apply these new strategies. This practice is important, but another important issue could be that study skills courses do not help students understand *why* these strategies are important and *how* they can be used effectively in different situations. Most study skills courses do not help students develop a system for analyzing their current learning situation, reflecting on what worked and what didn't work in the past, and choosing the strategies that are most likely to be effective *for them* in a specific circumstance.

A second criticism of study skills courses focuses on the message sent to students by calling these topics *skills* and covering them in a separate course. Specifically, the message is, "that there is a difference between studying successfully and learning, and that, if certain techniques are acquired, students can study successfully without deep engagement with the subject" (Wingate, 2006, p. 459). For example, common study skill instruction on taking a multiple choice test includes eliminating answer choices that use "always or never" and paying close attention to answer choices that appear to be opposite of each other. Although these tips may help students demonstrate what they have learned when asked specific questions on an exam, they may not help student do the requisite meaningful learning of the material prior to taking the exam.

There are courses that focus on helping students develop strategies for more meaningful material comprehension. In the Cole et al. (1997) organization, they are termed ***Learning to Learn*** and ***Critical Thinking*** courses. Often 3-credit hour, semester-long courses, instruction centers on understanding, evaluating, and organizing information, building and assessing arguments, and problem solving. This kind of generative thinking moves beyond the rote memory based instruction in study skills courses and prompts deep engagement in the content of the course to promote meaningful learning. However, important factors that impact engagement and use of these kinds of strategies are not commonly covered in learning to learn and critical thinking courses. Factors such as students' beliefs about themselves as a learner, their attitude toward college, and their ability to monitor whether or not they have actually learned something new influence learning and are generally not explicitly included in learning to learn and critical thinking course instruction. Including instruction about the factors that impact how we learn could put students in a better position to analyze their environment critically and adapt to it. Understanding how learning works and developing as autonomous, strategic, self-regulating learners who take control of and responsibility for their own learning is embodied within ***learning frameworks*** curriculum models.

Learning frameworks courses

Unlike study skills courses that offer lists of strategies for students to try out, learning frameworks courses are rooted in the study and application of learning theory to help students develop as self-regulated learners. Students engage with the theories researchers have developed and tested to explain the factors that impact learning (e.g., cognition, motivation, regulation, beliefs), analyze their own strategic learning thoughts and behaviors in light of these theories, and use all of this knowledge to create a toolbox of strategies that can help them navigate their academic (and personal) environments. In a sense, learning frameworks course content is designed to help students understand *why* the study skill and learning to learn strategies work and help students *develop* an ability to monitor and regulate their own learning.

The learning frameworks course in this study is a semester long intervention that has demonstrated strong positive outcomes. Students typically enroll in this course in response to poor academic outcomes in college or in an attempt to prevent doing poorly in college. In their analysis of persistence and completion rates of students who had completed the learning frameworks course, Weinstein et al. (1999) found that students who successfully completed the course in either their first or second semester in college had a five-year graduation rate of 71% compared to the general student population rate of 55%. Weinstein et al. (1999) also found that the significant difference in graduation rates between students who completed the learning frameworks course and the general population of undergraduate students remained, even after accounting for students' verbal and mathematics scores on the Scholastic Aptitude Test in the analyses.

Research-based learning theories lie at the heart of learning frameworks courses. A closer examination of two of these theoretical models, both of which were at the core of the learning frameworks course used in this study, follows: social cognitive theory and the model of strategic learning.

Theoretical Foundations

Social Cognitive theory

In 1986, Albert Bandura introduced social cognitive theory, building from his earlier work studying the mental processes associated with learning and motivation. In general, cognitive theorists stress the importance of mental processing of information and beliefs in organizing and acting on one's environment. Cognitive theorists conceptualize motivation as an internal construct, not directly observable except through its products. And, within cognitive theories, external stimuli (e.g., loud noises, notes on a chalkboard) are considered pieces of information that must be acted upon so that the processed information can be incorporated into an individual's existing belief system, therefore giving the stimuli meaning.

Bandura's (1986) social cognitive theory extended earlier cognitive theories and defined human behavior in terms of continuous, dynamic, reciprocal interactions between cognitive, behavioral, and environmental influences. Bandura also advanced the notion that individuals are proactive, engaged agents who can make things happen by their actions. Individuals are, therefore, products of and producers of their own environments and of their social systems. Within social cognitive theory, individuals' self-beliefs enable them to exercise control over their thoughts, feelings, and actions, and what they think and feel influences how they behave (Bandura, 1986). Thus, it is important for students to understand their thoughts, feelings, and actions in addition to understanding how these things interact with each other to influence future thoughts and behaviors.

These elements are fundamental to the learning frameworks course studied here. First, the goal of the course itself is for students to become proactive, engaged agents who take responsibility and control for their learning. Second, instructors teaching the course employ andragogical practices that acknowledge the continuous, dynamic, and reciprocal interactions between cognitive, behavioral, and environmental influences. Throughout the semester, students work in small groups with stable membership, collaborating and creating knowledge with the help of texts, media, and other artifacts curated by the instructors. They engage in ongoing self-reflection and experimentation with many learning strategies, sharing their experiences with peers and learning from the experiences of their peers in order to identify those strategies most effective for themselves.

Model of Strategic Learning

A second conceptual framework in this study is the Model of Strategic Learning (MSL), the core idea guiding the curriculum used within the learning frameworks course studied here as well as many other learning frameworks courses (Hodges et al., 2001; Weinstein et al., 2009; Weinstein, Husman, & Dierking, 2000). Originally developed by Claire Ellen Weinstein in 1979, the more recent version of the MSL (2009) includes individual and environmental factors that have been shown to impact learning, an appropriate conceptual foundation for learning frameworks courses because the scope of these courses is on engaging students with research-based models for how learning works (Hodges et al., 2001).

Research-based elements that impact learning are organized within the MSL under four components: skill, will, self-regulation, and the academic environment. In order for an element to be included in the model, the following conditions must be met: there must be an established research base demonstrating a causative link between the element and academic success, the element must account for a meaningful improvement in academic success, and it must be amenable to change (Weinstein et al., 2009). Though the four components of the model remain unchanged since the model was introduced, additions and clarifications of the individual elements within each component have happened as researchers expand the empirical evidence in motivation and the learning sciences.

The MSL is best viewed as an emergent model, promoting a holistic view of student learning in which the greatest impact on learning is a result of the interactions among several elements in the model, not usually as a result of one individual element by itself (Weinstein, Tomberlin, Julie, & Kim, 2004). For example, knowing how to process new information is an element within the skill component. Developing this skill on its own will positively impact student achievement, but that impact will be even stronger if a student has the desire to process new information effectively (desire/motivation as a part of the will component) and monitors their progress toward learning the new information (an element within the self-regulation component). The motivation to study (will) without knowledge and use of effective strategies to employ while studying (contained in the skill and self-regulation components) will not result in as successful an outcome as there will be when all are combined. And, as the model shows (see Appendix A), the learner, complete with individual strengths and weaknesses, likes and dislikes, and prior learning experiences, is at the heart of the model. The interaction among elements is directed by the learner and viewed through the lens comprised of his/her prior experiences. Thus, to get the most out of using the MSL to improve student success, the learner must develop awareness not only of the elements within the four components but also how he/she individually controls each of those elements.

Within this study, the LASSI (Learning and Study Strategies Inventory) (second edition, 2002) is one of the instruments used to measure students' thoughts, beliefs, attitudes, and behaviors. The LASSI was designed to align with the MSL, and the scales and items within the instrument measure elements that fall within the skill, will, and self-regulation components. The following section outlines a sample of the research-based elements contained in the skill, will, and self-regulation components of the MSL, with attention to those aspects that are particularly salient for this study.

Skill component

Elements within the *skill* component address knowing *what to do* to learn and *how to do it* (Weinstein et al., 2009). Strategies described above as part of Learning to Learn course instruction (e.g., acquiring new knowledge by making the information personally meaningful, separating out important information from supporting information while studying, and preparing and taking tests effectively) are part of this component. In general, *skill* elements are the learning and thinking strategies that students use to create meaning, store information so it can be retrieved in the future, and monitor their learning progress.

The MSL presumes that personal and environmental influences impact decisions about "what to do" and "how to do it." Therefore, it is useful to think of *skill* strategies and skills as tools in a toolbox. The process of developing a diverse toolbox enables students to make mindful decisions about strategy preferences and effectiveness. And, having a well stocked toolbox (and the ability to develop additional tools as needed) enables students to resolve various academic challenges with a precise set of tools selected to meet the demands of that task. These strategies are included within the *skill* component as a *type of knowledge* students can leverage to organize and analyze information to make effective strategy choices.

In addition to knowledge about learning strategies, other types of knowledge useful for students to understand and leverage include knowledge of the *task* (what the assignment, presentation, or assessment is specifically asking them to do), what relevant *prior knowledge* they have relevant to that task (previous instruction on this content or previous experience with a similar assignment), and how they will use this information in the *future*.

Of particular importance in this study is a final type of knowledge, knowledge about personal characteristics that influence how easy or difficult it is to learn new information. Within the MSL, this collection of characteristics is referred to as *knowledge of yourself as a learner*. Knowledge of one's self as a learner incorporates academic self-concept (evaluations of ones strengths, weaknesses, unique qualities, and typical behaviors as a student) as well as personal preferences (such as favorite study locations and feelings about group work). Researchers have demonstrated that academic self-concept has direct and indirect effects on achievement (Marsh & Martin, 2011; Marsh et al., 2005), and that students often hold inaccurate assessments of their abilities and personal qualities (Dunning et al., 2004). Because the MSL is an emergent model, the impact of inaccurate assessment on one strategic learning factor could be amplified as the factors influence each other across model components as well. For example, overconfidence could lead students to believe they are prepared for an assessment, which could decrease their motivation to study (*will)* and avoid self-testing (*self-regulation)* to assess whether they have learned the new material. It is important to understand whether or not students' assessments of their learning abilities follows the same patterns as other self-perceptions' and, if so, if an intervention aimed at increasing students' knowledge of themselves is achieving this outcome.

Will component

Elements within the *will* component relate to students' motivation, attitudes, and interest in learning and achieving college success, their ability to cope with worry about school and academic performance, and their self-discipline, commitment, and willingness to do what needs to be done to achieve the outcomes they desire. Elements of this component focus on goals (setting, analyzing, committing to, and using them), emotions, creating a positive mindset toward learning, and avoiding self-sabotaging thoughts and behaviors.

Will elements are important because researchers have demonstrated that motivation (e.g., confidence, interest, and value) can influence actions and ultimately impact academic achievement. For example, a student who feels confident in his ability to speak in public is more likely to set higher standards for his work, put in effort to preparing for a speaking engagement, and respond more productively to negative feedback than would a peer with lower public speaking confidence. Enjoyment of a particular activity or subject has been linked to higher engagement in the task and persistence when challenged (Wigfield & Eccles, 1992), as is seeing the relevance and value of current activities to future goals and aspirations.

Bandura (1997) argued that motivation is based more on what an individual believes than what is objectively true. This argument is supported by educational researchers who have found that students' beliefs about their abilities are stronger predictors of their achievement than their actual ability (Pajares, 2008). Beliefs can be self-focused (e.g., "I am smart"), other-focused ("she is good at math") and context specific ("this class is a waste of time"). These beliefs can inform behavior and thought patterns, shape individuals' choices of which goals to pursue, and influence how they interpret and respond to environmental factors impact progress toward their goals. One particular belief that researchers have focused on in recent years is a students' belief about whether or not their intelligence can change.

Students who endorse a growth (or incremental) theory of intelligence believe that their academic abilities can be increased with effort whereas students who believe academic abilities cannot change are said to endorse a fixed (or entity) theory of intelligence (Dweck et al., 1995). Using a series of questions about whether students believe their achievement is a function of ability or effort, Dweck and Leggett (1988) demonstrated that students' beliefs about the malleability of their intelligence—that is, that intelligence can develop in part through students' own strategic efforts—shaped their academic achievement and engagement behaviors. As the field has grown, so too has the terminology associated with these constructs. *Growth, incremental*, and *malleable* are often used interchangeably, as are *fixed* and *entity*. Within this study, I use the term *growth mindset* to denote the belief that academic capabilities can change with effort and the term *fixed mindset* to denote the belief that academic abilities are a function of innate ability.

Positive academic behaviors, including greater class attendance, asking for help when faced with academic challenges, enjoyment of the academic process, and completing more challenging activities, have been linked to adoption of a growth mindset (Aronson, Fried, & Good, 2002; Tabernero & Wood, 1999; Wood & Bandura, 1989). In contrast, endorsing a fixed mindset belief has been linked to lower academic performance, a decreased likelihood of persisting in the face of academic difficulty, and avoidance of asking for help, even when doing so would be beneficial (Blackwell, Trzesniewski, & Dweck, 2007; Cury, Da Fonseca, Zahn, & Elliot, 2008; Dweck, 2008).

Students with a growth mindset may have a more accurate understanding of their knowledge level, as they are open to the idea that their intelligence will change, and they may, therefore, spend time engaged in reflection. They may be more likely to find value in participating in course activities aimed at helping them identify and change their strategic learning behaviors. And they may be more likely to incorporate feedback into making personal changes. On the other hand, students who believe that their intelligence level is fixed could disengage from reflecting on their own actions and thus be unaware of their true level of knowledge. Some evidence exists indicating that individuals with a fixed mindset are less accurate in assessments of their performance than growth mindset individuals (Ehrlinger & Shain, 2014). Thus, guided instruction in how beliefs impact learning could help even students with a fixed mindset to develop more accurate self-knowledge, which will positively impact their academic achievement. Specifically, this information will be useful because successful students draw on knowledge of themselves as a learner as they plan, monitor, and evaluate their own academic behaviors. This process, referred to as self-regulation, is the third MSL component and is discussed below.

Self-regulation component

In the MSL, the self-regulation component serves to harness the skill and will – to manage the whole learning process. Within the past two decades, self-regulation has developed into the construct used to explain purposeful behaviors, cognitions, and motivational practices behind the pursuing of learning goals, which, consequently influence academic achievement (Zimmerman, 1989). Examples of self-regulatory behaviors include the ability to direct and maintain attention on academic tasks, the use of reviewing and comprehension monitoring techniques to assess understanding, and the use of support techniques, materials, or resources to learn new information.

Self-regulated students are active throughout learning activities, mentally monitoring and exerting control not only over their actions but also exerting control over the cognitions, beliefs, intentions, and affect that underlie those actions. Mental monitoring and exertion of control are examples of cognitive and metacognitive processes (Schunk, 1994; Winne & Hadwin, 1998; Zimmerman, 2002).

Cognition refers to the internal processes functioning to enable individuals to perceive, remember, think, speak, and solve problems. Cognitive skills such as organizing ideas and making connections between concepts enable individuals to meet task demands and are especially important within learning situations. Metacognition encompasses higher order thinking that involves active control over cognitive processes used in learning situations (Flavell, 1976). Often simplified as "thinking about thinking," researchers distinguish between two components of metacognition – knowledge of cognition and regulation of cognition (Schraw, 1998). Metacognitive knowledge includes declarative knowledge, procedural knowledge, and conditional knowledge. Taking examples used to describe the *skill* component of the MSL, knowing about a specific strategy is an example of *declarative knowledge*, understanding the way you would use that strategy is *procedural knowledge*, and *conditional knowledge* refers to knowing which cognitive strategies to use when and why to use them. Regulation of cognition also includes three components – planning which resources and cognitive strategies to allocate to a specific task, regulating or monitoring progress toward learning goals, and evaluating the results of one's learning processes. Taken together, cognition and metacognition are the foundation upon which self-regulated learning theories are built.

Numerous self-regulation theories exist: Pintrich's General Framework for Self-regulation (Pintrich, 1989, 2000; Pintrich & Garcia, 1994), Boekaerts and Corno's Dual Processing Self-regulation model (Boekaerts, 1997; Boekaerts & Corno, 2005; Corno, 2001), and Winnie and Hadwin's (1998) Sociocultural Perspective of Self-regulated Learning but most share at least a few overlapping ideas. As it aligns with Bandura's Social Cognitive Theory, this study relies most closely on Zimmerman's Social Cognitive Model of Self-regulation (Zimmerman 1989; 2000). In this model, self-regulated learning is a cyclical process during which the phases of the cycle interact and influence each other.

As Zimmerman (2000) conceptualized it, learning proceeds through three phases – forethought, performance, and self-reflection. In the forethought or planning phase, individuals select appropriate learning strategies to employ in order to achieve learning goals. Self-motivation beliefs (self-efficacy, goal orientations, outcome expectations, and value) and task analysis (goal setting, strategic planning) are key within this phase. In the performance phase, individuals deploy the selected strategies, continuously monitoring task performance and comprehension. Finally, in the self-reflection phase, individuals evaluate the product of the performance stage, judging, reacting, and determining to what the outcome should be attributed. These evaluations feed forward into the forethought phase of the next iteration of the self-regulation cycle. Paris and Paris (2001) asserted that a lack of knowledge and a lack of experience are usual explanations for students' poor self-regulation and other researchers have noted that the self-regulation cycle can be undermined when students rely on inaccurate or incomplete information. This can clearly be seen in the literature around self-regulatory monitoring. Many studies have demonstrated the importance of monitoring for learners of all ages and abilities use *monitoring* (Dunlosky and Ariel, 2011), but few have addressed the importance of monitoring *accuracy* to learning (Dunlosky and Rawson, 2012).

Researchers believe that self-regulation can be developed (Zimmerman, 2000; Zimmerman, Moylan, Hudesman, White, Flugman, 2011) and that metacognitive abilities are considered malleable and independent of general intelligence (Pressley & Ghatala, 1990). Most regulation research focuses on learning and achievement goals (Boekaerts & Corno, 2005), producing a large literature base connecting self-regulation with academic performance. Despite positive associations between effective self-regulation and academic performance, self-regulation is rarely included in classroom instruction or listed as an explicit goal on which instructors focus in their courses (Hofer & Yu, 2003; Loyens, Magda, & Rikers, 2008). When instruction in self-regulation is explicit within classroom instruction, there is a significant improvement in learning, in use of regulatory skills, and in understanding how to use those skills (Brown & Palincsar, 1989; Cross & Paris, 1988).

In their metanalysis of the effectiveness of learning strategy instruction on academic performance, Donker et al. (2014) identified that teaching metacognitive strategies had the greatest impact on helping students become self-regulated learners. Though the 95 studies included in their analysis were pooled across multiple content domains (writing, science, mathematics), these researchers concluded that teaching students which strategies to use and how to apply them (declarative knowledge) and also when and why to use them (procedural and conditional knowledge) is valuable in improving academic performance. Additionally, they found that low and high SES students, gifted students, students with special needs, and "regular" students all benefitted from strategy training.

Because this direct learning strategy instruction can take many forms, a few suggested by Paris and Winograd (1990) are offered here. First, individuals can be taught self-regulation by participating in explicit discussions or reflection exercises that focus on the definition and practices involved in self-regulation. A second form would be to expose students to self-regulation indirectly through modeling. Direct assessments and discussions focusing on personal growth offer a third alternative for increasing self-regulated behaviors. Learning frameworks courses leverage these pathways and provide explicit instruction on self-regulation theory and research as well as provide opportunities for personal growth through analysis of self-knowledge and comparisons of subjective feelings and beliefs to objective data.

Self awareness

One specific area of personal growth targeted by some learning frameworks courses is students' self-awareness. This can include their awareness of what they need to do to complete academic tasks and how well they performed on an assignment or an assessment, but it also extends to their awareness of other factors about themselves as a learner. For example, their general attitude and motivation for succeeding in school and performing the tasks related to school success, their ability to cope with academic anxiety, the degree to which they accept responsibility for performing the specific tasks related to school success, and the methods they know and can use to help add meaning and organization to what they are trying to learn. Understanding oneself as a learner and understanding academic task requirements can influence how students allocate study resources (time, materials) and which study strategies to select for the task at hand. However, if students rely on in accurate perceptions, their ability to be a strategic learner could be compromised. Accurate monitoring can influence whether or not a student decides to persist either by continuing to implement the original plan or by adjusting effort or strategies in response to new information. Dunlosky and Rawson (2012) hypothesized that overconfident students may prematurely stop studying which can lead to a lower level of learning and therefore poor performance on an examination. In finding that students who were less overconfident when evaluating their learning retained more information than their less confident peers, the researchers found support for their hypothesis.

Other studies link accurate self-assessments to efficient allocation of study time and better academic outcomes (Marsh et al., 2005). For example, Schraw (1994) noted that college students' judgment of their ability to monitor their reading comprehension was significantly related to their observed monitoring accuracy and test performance. And, in another study investigating the effects of metacognitive monitoring on reading comprehension, Thiede, Anderson, and Therriault (2003) found that more accurate monitoring led to improved self-regulation that, in turn, translated into improved performance. Closer examination of students' calibration – that is, the accuracy of students' self-assessments on factors known to influence learning - would help expand our understanding of the quality of self-regulation behaviors.

Calibration

Calibration is an essential cognitive and metacognitive process that involves creating an internal assessment and comparing it against a standard (Nietfeld et al., 2006;

Winne, 2004). Most calibration research focuses on individuals monitoring their performance relative to a standard of achievement within a specific content domain (e.g., writing, mathematics), with calibration often measured as the difference between an individual's predicted and actual performance (Bol et al., 2005; Lin & Zabrucky, 1998). Calibration researchers have also studied students' evaluations of how easy or difficult it will be to meet the standards of a task, how confident students are that they correctly answered a question on an assessment they just took, and whether or not they would be able to answer questions about a topic correctly on a future assessment (Winne, 2004).

In the above examples, calibration is measured by the degree to which self-perception matches actual performance; this is referred to as *absolute accuracy*. Calibration researchers use both measures of absolute and relative accuracy, depending on their research questions as they represent different aspects of metacognitive monitoring. To measure *relative accuracy*, or *discrimination,* researchers ask participants how confident they are that they answered a specific item correctly (an absolute accuracy measurement), and then ask them if they are more or less confident in answering this item correctly as compared to correctly answering another item. According to Hacker et al. (2011), only small correlations have been found in studies that compare absolute and relative accuracy, leading these researchers to conclude that the two types of accuracy tap into different aspects of metacognitive monitoring. Measures of absolute accuracy should be used to answer research questions that involve comparing judgments with actual performance and investigating changes in monitoring accuracy related to an intervention, like the ones in this study, as these measures are more sensitive to individual differences (Maki, Shields, Wheeler, & Zacchilli, 2005). In this study, calibration accuracy is the absolute difference between predicted (or self-assessed) performance and actual performance.

Whereas accuracy measures the magnitude of deviations between predicted performance and actual performance, calibration *bias* measures the direction of that deviation. If an individual's predicted performance is greater than the actual performance, the individual is positively biased, or overconfident. On the other hand, when actual performance exceeds predicted performance, the individual is said to be negatively biased, or under-confident. As the difference between perception and actual performance decreases, calibration improves (Nietfeld et al., 2006).

In most calibration research, participants are asked to make predictions about their current and future performance. Calibration *predictions* are made prior to engaging in an activity or completing an assessment. *Postdictions,* or assessments made after completing an assessment (either immediately after or with some delay) but before receiving objective feedback about performance, are also used in calibration research. Predictions and postdictions tap into different elements of the self-regulation process: predictions are particularly useful in the planning and implementing stages. Postdictions necessarily require that the event or assessment be complete and are, therefore, useful during the evaluative stage. Accuracy in both predictions and postdictions is important for strategic, self-regulated learners, but previous research shows that these kinds of self-assessments are often inaccurate and resistant to improvement.

Accuracy of self-assessments

Self-assessments tend to be inaccurate, and are most often positively biased. Individuals tend to overestimate their logical reasoning and English grammar abilities (Kruger & Dunning, 1999), knowledge of facts (Lundeberg et al., 2000), and their academic abilities (Miller & Geraci, 2011). In one study of exam performance calibration, Hacker et al. (2000) found that many undergraduate students predicted they would earn exam scores that were more than 30% higher than their actual scores. Aside from inaccurate perceptions of knowledge mastery, students can also be poor estimators of how much time it will take to complete a task. In one study that speaks to these results, researchers asked undergraduate university students to predict how long it would take them to complete their honors thesis. The students predicted it would take, on average, 33.9 days; a statistically different length of time from their actual 55.5 day average (Buehler, Griffin, & Ross, 1994). Most often in the calibration literature participants are making accuracy judgments with respect to general knowledge (e.g., grammar, assessments of humor, factual information on exams) or skills (e.g., adding double digit numbers). However, social psychology researchers who have found that students hold *unrealistically optimistic* perceptions of academic outcomes echo these findings of positively biased, inaccurate self-assessments. Instead of working with general knowledge and skills, this field directs attention inward to individual capabilities.

Unrealistic optimism refers to the mistaken belief that personal negative outcomes are less likely to occur than is objectively warranted. Researchers in this field have found that students overestimate the grades they will achieve on forthcoming exams (Shepperd, Grace, Cole, & Klein, 2005), overestimate their starting salary after graduation (Shepperd et al., 1996), and underestimate the time to complete a task such as writing a report (Koole & Spijker, 2000). These misperceptions could lead to a host of suboptimal academically related thoughts and behaviors. For example, students who overestimate their preparation for an exam (e.g., positive calibration bias) may believe they have adequately prepared, when in fact they are under the illusion of knowing and they have stopped preparing too soon. On the other hand, students who underestimate their performance may make poor time management decisions, assuming that they have not yet mastered material. Inefficient use of time and suboptimal strategy selection could, in turn, negatively impact academic achievement.

Both high and low achieving students tend to overestimate their performance. However, calibration accuracy has been shown to vary by achievement level in that high achievers are more accurate in their estimations than are low achievers (Bol et al., 2005; Dunning et al., 2004; Hacker et al., 2000). The leading interpretation for this finding is two-fold: high performers underestimate because they assume that others perform at the level they do and low performers overestimate because they lack metacognitive insight. In addition to not having content knowledge, low performers are unaware that they lack this knowledge. Although some amount of overestimation of skill or ability could be useful as a protective mechanism that leads students to persist when faced with small challenges, the large distortions seen with low performing students could lead to poor study-related decision-making because those decisions are then based on incomplete or erroneous information. Low performers' consistent overestimation may be more complicated than simply a lack of metacognition, however.

Low performers' predictions that they will do much better than they actually do, even in the face of counterinformation, are sometimes referred to as "unskilled and unaware" (Kruger & Dunning, 1999). These students may be relying on "pseudo relevant" information during their decision making; although the information is factually sound, it does not directly relate to the task at hand. Miller and Geraci (2011) targeted the "unaware" claim and, consistent with prior calibration research, found that low performing students were overconfident in their ability, but, unlike most findings, the researchers found that low performing students were in some way aware of their deficits. In two studies, the researchers parsed out what they termed functional overconfidence (error in predicting that one would preform better than they actually do) and subjective overconfidence (being overly certain of one's prediction). Researchers asked students to predict their grades on course exams and to rate their confidence in their predictions.

Arguing that if low performers really were unaware of their deficits, they would be at least as confident in their predictions as the high performers. As predicted, low-performing students displayed a greater *functional overconfidence* than did high-performing students on both outcome measures – exam grades and prediction confidence. However, low-performing students were less *subjectively overconfident* in their predictions than were high performing students, leading researchers to conclude that low-performing students have at least some awareness of their ineptitude. Miller and Geraci (2011) also examined whether functional and subjective overconfidence might change over time and with course experience. They concluded that despite having experience with the course materials and exams, low performing students continued to show more functional overconfidence than high-performing students did. Low performing students' level of subjective confidence also persisted; they continued to be less subjectively confident in their predictions than high-performing students.

Researchers have also found differences in calibration based on the timing of self-assessment. Take, for example, a study of test performance calibration. Prior to taking an exam, researchers can ask participants to predict how many questions they will answer correctly. After participants complete the exam, researchers ask participants to assess how many questions they actually answered correctly. More information is available for participants to consider when making the postdiction assessment – they now have actual knowledge of the material and of the questions included on the exam. Presumably, they should consider this information when making their postdiction. In their semester long study of achievement calibration and explanatory style, Bol et al. (2005) found that postdictions were indeed more accurate, but for the most part they stayed stable during an intervention aimed at improving both prediction and postdiction assessments.

Correcting these inaccuracies can help all students be successful, but will be particularly useful for students who often struggle academically and lack parental guidance to help them assess how "on track" they are.

Influences on calibration accuracy

Domain familiarity

Maki and Serra (1992) tested the hypothesis that domain familiarity was highly correlated with confidence assessments. They provided undergraduate psychology students with a series of text title and one-sentence passage description pairs and asked students to predict performance on a short quiz over the content of the passage. Students then read the passages, again predicted their performance (postdiction assessment), and then took the quiz. The researchers reasoned that the initial prediction ratings were based on familiarity with the domain and that the postdiction would be based less on domain familiarity and more on the text itself. The researchers interpreted the increased accuracy of the postdiction as an indication that students were using the knowledge gained from the text to make more accurate assessments of their future performance. As content knowledge increased, so did the accuracy of judgments about content mastery (Maki & Serra, 1992), leading researchers to conclude that improving content mastery can improve judgments. Other researchers have also found that judgments of learning were more overconfident for better known than for lesser-known topics (Shanks & Serra, 2014). Shanks & Serra also found that domain familiarity was linked to student's decisions about how long to study for and what topics to study during that time. More specifically, that "participants effectively use their domain familiarity as a basis for their JOLs (judgments of learning) and restudy choices, but to some extent overuse this factor to assess their learning and underuse it to guide initial study" (p. 445).

Subjective experience

Students do not approach novel tasks as blank slates. Rather, they bring fragments of knowledge gained from experiences across many domains and their interpretation of the current situation is viewed through the lens created by these fragments. Bandura (1997) argued that this collection of interpretations influences an individual's self-efficacy; that is, their confidence in his or her ability to do what is needed in the current situation. According to Bandura, self-efficacy is more influential than what is objectively true about those capabilities. Other educational researchers have supported this assertion, reporting their own findings that students' beliefs about their abilities are stronger predictors of their achievement than their actual ability (Pajares, 2002).

Individuals' confidence beliefs are influenced by many sources; one of the most powerful has been shown to be their interpretation of their own prior successes and failures (Pajares, 2008). These interpretations of prior experiences influence one's beliefs about his or her capability to engage in subsequent activities and the likelihood of success at that future activity (Usher & Pajares, 2008). For subsequent tasks that are similar to the previous tasks, these judgments are likely to be beneficial. However, problems may arise if students fail to see differences between a new task and the tasks they already feel highly confident about. In some respects, calibration depends on the extent to which memories – such as previous experiences and processes – are accessed. If students approach a new learning situation not remembering a prior experience or considering many different learning strategies they could use to complete the task, their learning will be hampered.

Other researchers have noted that people base their perceptions about quality of future performances in part on preconceived notions they have about their skill (Dunning, 2011, p. 55) and people are more likely to rely on subjective rather than objective data when deciding what action to take in a situation (Dunning, 2011). Thus, if a student enters a situation erroneously believing he or she has no skills to help him or her be successful, this belief is unlikely to be overridden by objective data that could be used to accurately self-assess or assess the environment. This is precisely the aim of learning frameworks courses – to increase awareness and use of relevant information in a self-regulated learners' decision making.

Interestingly, in contrast to the overwhelming evidence that humans are not well calibrated to their own abilities, it is Bandura's work that provides one example of a situation in which study subjects were very accurate in their predictions about their ability to perform a task. After working to desensitize patients with severe snake phobias, Bandura, Adams, and Beyer (1977) found a high correlation (.80) between the interactions with a snake that participant's thought they would be capable of doing and what they subsequently were actually able to do. Dunning (2005) highlights the fact that participants responded specific questions about specific behaviors within a well-defined situation (e.g., can you pick up a snake) instead of general beliefs (e.g., are you a good snake handler) as facets that may have contributed to more accurate predictions about actual behaviors. As paralleled in this study of strategic learning, there are factors that are more concrete and some that are more abstract.

Strategy instruction

Bol & Hacker (2012) assert that calibration tends to be stable and that "repeated calibration practice … does not seem to enhance accuracy, particularly among low-achieving students" but that "instruction on monitoring and calibration were found to be effective (p. 487). Other researchers have shown that self-assessment accuracy improves when learners receive feedback (Brtannick, Miles, & Kisamore, 2005; Glenberg &

Epstein, 1985) and that accuracy does improve when students are given an opportunity to practice using reflection strategies (Bol et al., 2005).

In a semester long study on the effects of strategy instruction on monitoring accuracy, Nietfeld and Schraw (2002) provided participants with direct instruction on strategies for solving probability problems. This direct instruction included "explaining the rule or concept, identifying when a rule or concept was applicable, and modeling the problem-solving process for sample problems" (Nietfeld & Schraw, 2002, p. 137). Following the direct strategy instruction, participants answered a series of probability questions. For each question, they were given four answer choices and asked to mark their answer as well as use a 100-point line to express how confident they were that their chosen answer was the correct answer. They found that participants who received the strategy training got more answers correct and their confidence predictions were more accurate than those who did not receive the strategy instruction. Interestingly, researchers also demonstrated that strategy instruction did not influence calibration bias (participants were still over- or under-confident). Strategies for monitoring comprehension were not part of the training, yet monitoring accuracy improved as a result of the strategies that were taught. As is customary, this study was conducted in a laboratory environment and focused on domain specific strategy use.

In a separate semester-long study of a strategy intervention, Nietfeld et al. (2006) investigated the effects of monitoring exercises and feedback on calibration. This time, instead of conducting the study in a laboratory environment, the researchers collected data from students enrolled in an undergraduate educational psychology course. They were interested in assessing the impact ongoing monitoring strategy instruction had on exam performance and calibration. Each week students in the treatment condition completed a set of monitoring exercises that included rating their understanding of the day's content (100-point scale), identifying class concepts that were difficult for them to understand and what steps they would take to improve understanding of those concepts, and answering multiple-choice questions based on the previous day's material. Students answered three multiple-choice questions in each class and used a 100-point scale to record how confident they were that they had answered the question correctly. These review questions were discussed and answered at some point during the session and students were encouraged to compare their actual performance to their confidence judgment. During each of the four in-class examinations, all students (control and treatment conditions) completed confidence judgments for each item. All students were also allowed to examine their graded exam along with the confidence ratings they had made and to ask questions about any content that may still have been unclear.

At the end of the semester, researchers compared students in the control and treatment conditions. Overall, they found that students improved their calibration accuracy and that the improvement in calibration accuracy related to an increase in performance on class tests. They found that significant differences in calibration and exam performance emerged by the second of the four tests, but were not present at the first exam, leading researchers to conclude that the impact of this strategy intervention took time to manifest. Building off of this evidence that strategy instruction can influence accuracy and achievement, and that calibration is amenable to change, the intervention in this study could provide additional information useful in constructing meaningful strategy instruction.

Calibration and growth mindset

Most calibration research focuses on cognitive and metacognitive elements. For example, to understand the influences on comprehension calibration, researchers manipulate text (hard/easy passages, unfamiliar/familiar topics) and task factors (recall words, answer questions, summarize passage). Recently, however, researchers have started to incorporate social cognitive elements in their work, recognizing a need to include individual-level factors such as beliefs in their study of calibration (Stolp & Zabrucky, 2009). This is important as self-regulation in general is influenced by an individuals' beliefs, and accurate calibration necessitates that students continue to reflect on their performance as it evolves in order to update beliefs about themselves and what they know appropriately. It may be that their beliefs about whether or not their intelligence can change will influence this process.

Thus, students who believe that, with effort, they can earn higher grades and improve their academic standing are said to have a "malleable" sense of intelligence, or a growth mindset (Dweck et al., 1995). These students may have a more accurate understanding of their knowledge level, as they are open to the idea that their intelligence will change and may, therefore, spend time engaged in reflection. Students who believe that their intelligence level is fixed, on the other hand, could disengage from thinking about their own actions (e.g., studying for an exam) and thus be unaware of their true level of knowledge and/or be unwilling to do the kind of reflection to grow as an effective learner during a semester-long course.

First generation college students

First generation (G_1) college students have been a central focus of higher education researchers and practitioners in part because these students are more likely than their peers to not attend college and not complete a degree if they do enroll. For reasons outlined below, college students who are the first in their family to attend college might particularly benefit from explicit strategy instruction focused on building accurate self and other perceptions.

Defining first-generation

Federal guidelines (U.S. Department of Education, 1998) denote G_1 students as those whose parents have obtained at most a high school education; using this definition, close to 36% of beginning college students are classified as first-generation students (Ho & Wei, 2011). An alternate, widely used, definition allows for parents to have attended some college and to have obtained an associates' degree. With this definition that parents must not have obtained a bachelor's degree, low-income G_1 students make up an estimated one-quarter of all postsecondary students (Chen & Carroll, 2005). By either measurement, G_1 students comprise a large number of postsecondary students. Researchers have found differences in views and beliefs about college between students whose parents have some college and those whose parents obtained a bachelors degree (Lee, Sax, Kim, & Hagedorn, 2004).

First-generation student characteristics

G_1 students disproportionately come from lower income families and are more likely to be ethnic minorities (Nunez, 1998; Terenzini et al., 1996). Additionally, low-income G_1 students tend to be older, female, are less likely to receive financial support from parents, and more likely to have multiple obligations outside college, like family and work, that limit their full participation in the college experience (Engle & Tinto, 2008). These students are also more likely than their advantaged peers to delay entry into post secondary education after high school and to live off campus. Although previous research has shown that these demographic and enrollment characteristics are risk factors that interact with G_1 status to impact degree attainment (Engle & Tinto, 2008), G_1 status alone has been linked to important educational outcomes. For example, having a parent with a bachelors' degree has been shown to be a significant predictor of postsecondary enrollment, even after family income, educational expectations, and peer influence was taken into account (Choy, 2001; Pascarella et al., 2004).

College persistence and completion

G_1 students are less likely to apply to college, less likely to attend college, and more likely to attend a less selective institution if they attend at all (Choy, 2001; Pascarella et al., 2004). In their examination of access to postsecondary education among high school graduates, Berkner and Chavez (1997) found that enrollment at a two-year institution was higher for G_1 students (56%) than for continuing generation students (23%).

Once in college, G_1 students earn lower grades, complete fewer credit hours, take fewer natural science and mathematics courses, and opt to major in vocational and technical fields instead of engineering, humanities, or social sciences when compared to their continuing generation peers (Bromberg & Theokas, 2014; Chen & Carroll, 2005; Pascarella et al., 2004). Unfortunately, researchers have also found higher first-year drop out rates among G_1 students when compared to non- G_1 students, as well as less persistence toward a degree in both two-year and four-year institutions (Berkner et al., 2000; Billson & Terry, 1982).

Warburton, Bugarin, and Nuñez (2001) quantified this persistence difference, finding a 3-year persistence rate gap of 15% between first-generation students (73%) and second-generation students (88%). Extended over a longer period of time, the persistence rate for first-generation students is even lower. In a longitudinal study conducted by the National Center for Education Statistics using data from postsecondary institutions in the United States from 1992 through 2000, 43% of G_1 students left college without obtaining a degree (Chen & Carroll, 2005). More recently, Ishitani (2003) conducted a longitudinal study focused on G_1 student attrition and found that, even after controlling for race, gender, high school grade point average (GPA), and family income, the risk of attrition in the first year among G_1 students was 71% higher than that of students with two college-educated parents. These data show that if G_1 students make it to college at all, they struggle to persist and complete a degree.

Drivers of academic vulnerability

Why do G_1 students struggle in college? One hypothesis is that these students lack the social capital that would afford them access to important information about the culture of higher education and strategies for navigating the post-secondary environment. Continuing generation students may be more familiar with the expectations and demands of college after listening to family members' academic histories (Collier & Morgan, 2007). Parents of continuing generation students may disclose important information about what it takes to be successful in college (e.g., time management, the bureaucratic operations of higher education, the culture of higher education). This helps their children develop appropriate approaches for dealing with teachers, peers, and navigating the higher education environment, giving these students a leg up over students whose parents do not have similar experiences to share (Thayer, 2000; York-Anderson & Bowman, 1991). An alternate to this hypothesis is described later in this chapter.

The transition from high school to college is more challenging for G_1 students who experience all of the anxieties and difficulties that continuing-generation students do, but also must navigate cultural, social, and academic transitions that less frequently manifest as issues for continuing-generation students (Rendon, 1992; Terenzini et al., 1996). In their work studying the high school to college transition, Kirst and Venezia (2004) found that in general college-bound students are more concerned with getting *into* college than being successful in college and that low-income students had more significant misunderstandings of what it would take to be successful once in college.

Although some struggles with the transition are expected, low-income G_1 students may be at a disadvantage when these misperceptions of the workload and how to navigate the environment are not corrected. G_1 students are more likely to fear failing out of college and to feel less prepared for college than their continuing generation peers. Additionally, they believe they need to log more hours studying than their peers (Van T. Bui, 2002). So even when G_1 parents are supportive of their child's decision to pursue higher education, they may not be able to address their fears or reframe their perspective on the college experience. And, their well-meaning encouragement may even be detrimental to proper preparation for higher education if it does not correct inaccurate beliefs about what it takes to be successful in college.

Another explanation for why G_1 students struggle is that they are less academically prepared to enter college (Choy, 2001; Warburton et al., 2001). Approximately 15% of students with at least one degree-holding parent are underprepared for college compared to 49% of students whose parents had never attended college (Choy, 2001; Warburton et al., 2001), and a majority (55%) of first-generation students take remedial college courses (Chen & Carroll, 2005). Researchers have identified students' patterns of engagement in high school as one factor that can explain these tangible outcomes.

Engagement in high school

First-generation students tend to be less engaged in high school in general (Terenzini et al., 1996); specifically, they spend less time socializing with peers and teachers. It is through these interactions that important information useful in setting expectations and understanding the realities of college are transmitted. As a result of enrolling in less rigorous courses and not engaging with faculty and peers in high school, first-generation students are not developing the strategies and skills (e.g., studying in groups, reaching out to faculty and peers for help, and using support services) associated with success in college. This, in turn, impacts their performance and persistence rates to a failure to use strategies and skills (Billson & Terry, 1982; Nunez, 1998; Pike & Kuh, 2005; Terenzini et al., 1996).

An alternate hypothesis

As can be seen in the above discussion, the preponderance of G_1 research treats G_1 status as a deficit – something that puts these students at a disadvantage compared to students with parents or other close family that have college experience. Adopting a deficit approach that uses generational status, race, and socioeconomic indicators to explain differences in student achievement, retention, and persistence has helped researchers and IHEs to recognize that inequalities exist and has sparked good work to create success programs that target at-risk students. However, adopting this lens has done little to magnify the traits and personal assets that contribute to G_1 students' enrollment in, persistence during, and graduation from college. Yosso (2005) argues that, by focusing only on what underrepresented minority groups may lack, we miss opportunities to focus on the assets and strengths that move these students toward success.

While asset based models for first generation students is an understudied area in higher education, K-12 researchers have done more to showcase how unique skills can be classroom assets, not deficits. In this body of research, researchers acknowledge the cultural and family "funds of knowledge" students bring to the classroom and encourage educators to leverage these cultural and cognitive resources to provide culturally responsive and meaningful lessons that capitalizing on students' prior knowledge (Moll, 2001; Gonzalez & Moll, 2002). More broadly, Moll, Amanti, Neff, and Gonzalez (1992) assert that funds of knowledge influence how people deal with change, adapt to social and economic circumstances, and develop relationships to exchange resources, knowledge and skills.

In an exploratory qualitative study of first time in college students whose parents may have attended college, but did not graduate, Garrison and Gardner (2012) identify proactivity, goal direction, optimism, and reflexivity as personal assets G_1 college students honed in a variety of settings prior to college and use to their advantage to be successful in college. Researchers further identified resourcefulness, strategic thinking, self-reliance, practical realism, flexibility, persistence, positivity, hopefulness, self-confidence, insightfulness, compassion, gratitude, and balance as strengths that supported these assets. From interviews with G_1 students who had persisted after their first year of college, researchers gleaned that G_1 students, "repeatedly accessed expertise from critical adults to help them navigate their personal and academic dilemmas … obtained information or help from others when necessary (and) thought carefully about the facts in order to make effective decisions." These thoughts and behaviors are critical to college success and they align with what educational policy researchers St. John, Hu, and Fisher's (2011) highlight as essential in academic capital formation.

The academic capital formation framework seeks to capture the "social processes that build family knowledge of educational and career options and support navigation through educational systems and professional organizations" for underrepresented students. The process of forming academic capital can be either promoted or inhibited by the beliefs and practices of students, families, or schools and can include envisioning one's self and family as college students, understanding the role college courses have in preparing for graduate education and the workforce, and using one's resources to identify and pursue appropriate pathways through education systems. These are behaviors and thoughts essential for success for all students, and may be even more so developed in the sample population used in this study.

First-generation students and calibration

Standards play an important role in calibration because they provide information against which a self-perception is evaluated. Knowledge of the standards for performance in college is derived from personal and vicarious experiences. As they begin college, neither continuing generation nor first-generation students have personal experiences of college, but continuing generation students have had the opportunity vicariously to acquire knowledge of college standards and expectations through conversation with family members about their own college stories. As first-generation and continuing-generation students persist through college, they continue to have differential access to experienced family members who can provide guidance about navigating through the mundane and challenging aspects of higher education.

Festinger (1954) proposed that when objective standards are lacking, individuals assess their abilities and opinions by comparing themselves with similar others. And, even when standards are available, individuals across their lifespan gravitate toward making social comparisons when assessing their abilities (Suls et al., 1991). Therefore, in the absence of this vicariously acquired knowledge, first-generation students will substitute these standards with comparisons that will lead them to make calibration assessments that are biased or inaccurate. Calibration can be improved, however, by correcting incomplete or inaccurate information (Winne, 2004). Learning frameworks courses help students build knowledge of the environmental, personal, and behavioral elements that influence learning in college courses, filling in missing information and correcting erroneous assumptions that first-generation students may have about how learning works.

Chapter Three: Research Questions and Method

To explore whether a course devoted to helping college students become self-regulating, strategic learners influences the accuracy of students' self-knowledge, I addressed the following research questions and hypotheses.

Research Question 1

Does students' calibration accuracy improve from the beginning to the end of a semester-long strategic learning course?

Hypothesis 1a

At the start of the semester, students will not be accurate predictors of their strategic learning abilities.

Hypothesis 1b

At the start of the semester, the least strategic students' estimates of their strategic learning capabilities will be less accurate and more overconfident than their highly strategic peers.

Hypothesis 1c

At the end of the semester, all students will improve in their calibration accuracy. The least strategic students will demonstrate greater improvement in calibration accuracy than the highly strategic students.

Rationale

Self-assessments of academic abilities are often inaccurate. Individuals tend to be overconfident in their abilities, and overconfidence tends to be greatest for those who score below average compared to those with above average scores (Bol et al., 2005; Hacker et al., 2000; Kruger & Dunning, 1999; Miller & Geraci, 2011; Nietfeld et al., 2006). Interventions to increase calibration accuracy and decrease calibration bias have shown modest improvement (Hacker et al., 2000; Nietfeld & Schraw, 2002) by lessening factors that make assessments biased such as incomplete or inaccurate information (Winne, 2004). Reducing incomplete and inaccurate information upon which calibration judgments are based is at the heart of the learning frameworks course in this study. By taking personal assessments of strategic learning abilities, analyzing them, and studying theories of learning, cognition, and motivation, students build knowledge of the environmental, personal, and behavioral elements that influence learning. They were also taught specific strategies in each area and practiced using them. Therefore, at the end of the semester, their predicted score on the strategic learning variables of interest should have been more accurate. Because highly strategic students should start off the semester with more accurate self-assessments, I did not anticipate their change from the beginning to the end of the semester to be as large as it would be for the least strategic students in the course.

Research Question 2

Does generation status influence calibration?

Hypothesis 2a

At the start of the semester, generation status will influence the accuracy of student predictions.

Hypothesis 2b

At the end of the semester, generation status will not be a significant predictor of actual scores.

Rationale

The information disparity between first-generation (G_1) and continuing-generation students has been well documented by researchers and policy makers. As discussed above, first generation students often lack access to important information useful in setting expectations and understanding the realities of college. Additionally, because they are often not enrolling in rigorous courses and not engaging with faculty and peers in high school, first-generation students may not be developing the strategies and skills associated with success in college. However, it is possible that G_1 students, especially the G_1 students in this sample, have sought out or have otherwise had interactions with mentors who prompted them to think about their own preferences and capabilities as learners within the college context. Therefore, it is possible that for at least a few of the factors investigated in this study, there will be no differences between G_1 and continuing-generation student. If there is a gap at the beginning of the semester, G_1 and continuing students alike will benefit from studying the content of this course and the accuracy of their self-assessments should increase.

Research Question 3

What is the relationship between an individual's theory of intelligence and their strategic learning calibration?

Hypothesis 3a

Students endorsing a growth mindset will be more accurate in their predicted strategic learning abilities at the beginning of the semester.

Rationale

Prior research has demonstrated that self-assessments are more accurate among individuals with a growth mindset. And, if accuracy of strategic learning calibration improves as self-knowledge increases, then students' interpretations of feedback about themselves will influence whether or not their predictions become more accurate and less biased. Students with a fixed mindset can interpret failure as a permanent trait as they believe that, even with effort, they will not be able to improve their skills. For these students, negative feedback about their strategic learning could seem threatening and may be ignored. Students with a growth mindset, however, seek accurate feedback and look at feedback as helpful in determining how to improve next time. When these students fail, they work harder next time. Therefore, students with a growth mindset are less likely to feel threatened by the information about their strategic learning at the beginning of the semester and will see the course as an opportunity to develop their abilities, not as punishment for prior performance. The content of the course may not be as threatening to them as it could be for students with a fixed mindset. Students with a growth mindset may be more inclined to pay attention and use the information to help themselves become more strategic learners and are more likely to incorporate prior feedback into their future calibration attempts, thus improving their calibration.

Research Question 4

What is the relationship between accurate self-assessment and demographic factors such as family income and ethnicity?

Rationale

Many studies in the student success literature focus on these variables, but the calibration literature does not. Research questions 2 and 3 offer formal hypotheses of how common student success factors – generational status and theory of intelligence – impact the accuracy of students' self-knowledge. I proposed no such hypotheses for this research question. Instead, I included it to explore how these variables may or may not interact with other variables in this study.

Data and Procedure

Institutional Review Board

To answer the research questions outlined above, I used existing course data obtained from the instructors of record for sections offered Fall 2012 – Spring 2014. Student demographic information, including ethnic and racial identity, parental education, and family income, as well as academic information including assignment and exam grades were collected along with pre- and post-assessment data.

This study qualified for exempt status by the University Institutional Review Board. Data were originally collected as part of normal course operations and, once the data were selected for use in research, no additional information was solicited from the students. I obtained the data from course instructors via the course coordinator. I had no direct interaction with any of the students represented in the data set. Due to these circumstances, no psychological, social, or other risks were identified. I am housing the de-identified data on a locked, password protected laptop. The original data remain in possession of the course coordinator, as is required by the University for a set period following the conclusion of the semester.

Participants

Participants included the 507 students enrolled in one of several sections of a 3-credit hour, elective undergraduate educational psychology course at a large southwestern university. Students came from one of 22 sections of the course, representing a subset of the sections offered across four semesters of the course.

Setting

The overall goal for the course in this study is to help students become strategic, self-regulating learners who take responsibility for their academic lives and success. First-year and academically vulnerable students are often encouraged by their academic advisors to take the course in an effort to mitigate poor performance during their transition to college. Similarly, students on academic probation enroll in the course to identify the attitudes, thoughts, beliefs, and behaviors in which they currently engage, how these factors impact their learning, and to begin establishing new habits and mindsets that will contribute to successful academic and professional endeavors.

At the time the students participating in this study were enrolled, the course used the Model of Strategic Learning (MSL) as the conceptual model for engaging students with research-based factors influencing how learning works. Students were guided to build a toolbox of learning strategies that would leverage what they knew about the factors that influence learning. Understanding these theories was anticipated to help students have confidence that strategies can be effective and why they can be effective. Without this foundational knowledge, the learning strategies would seem flat, "declarative" statements (e.g., review your notes after class); the procedural and conditional elements important in self-regulation are shaped by an understanding of the theory. "Review your notes" is more powerfully communicated as "You only remember ~10% of what you study if you don't do anything with that information in the days after an initial learning episode. But putting ideas into your own words and making information meaningful to you is necessary for your brain to process the information effectively." This explanation was meant to lead to more meaningful action than the oft-repeated directive to "take notes." Additionally, the course provided a space for the students to become competent and confident in strategy use, congruent with Nietfeld et al. (2006) assertion that integrating metacognitive exercises within class contexts enhances future strategy use.

Measures

Learning and Study Strategies Inventory (LASSI). The LASSI, 2nd Edition is a diagnostic and prescriptive instrument consisting of 80 items evenly spread across 10 scales (Weinstein & Palmer, 2002). The scale was first published in 1987 after extensive norming using a nationwide college student population. It was revised 12 years later (there is now a third edition published in 2016). The second version of the instrument was used in this study. The items focus on the thoughts, beliefs, attitudes, and behaviors that relate to successful learning and are amenable to altering via intervention. The 10 scales align with the three Model of Strategic Learning components described above: skill, will, and self-regulation. For each item, students respond on a 5-point Likert scale ranging from 1 = Almost never true of me to 5 = Almost always true of me. A brief description of the scales is included in Table 1.

As previous researchers have noted, the LASSI instrument is one tool that could be used as part of a learning strategies intervention – both as an influencer of change that increases students' awareness of their current learning strategies and in an evaluative capacity as an assessment of the effects of the intervention (Sizoo, Malhotra, & Bearson, 2003). Flowers, Bridges, and Moore (2012) note that the LASSI can be administered at the beginning and end of an academic support program in order to measure the "accrued gains in study skills and study behaviors" (p. 156). Table 1 identifies the LASSI scales, provides a description for each scale, and notes which component of the Model of Strategic Learning that component fits under. Table 2 provides sample scale items and the scale reliabilities as supplied by the scale creators. This information comes from the LASSI (2nd edition) user manual (Weinstein & Palmer, 2002).

Table 1: LASSI scales descriptions

Scale	Description	MSL Component
Anxiety	Coping with worry about school and academic performance	Will
Attitude	Attitude and interest in college and achieving academic success	Will
Concentration	Ability to direct and maintain attention on academic tasks	Self-regulation
Information Processing	Use of strategies to help learn new information	Skill
Motivation	Self-discipline and willingness to work hard at academic tasks	Will
Selecting Main Ideas	Skill at identifying important information for further study	Skill
Self-Testing	Use of reviewing and comprehension monitoring techniques to assess understanding	Self-regulation
Study Aids	Use of support techniques, materials, or resources to help learn new information	Self-regulation
Test Taking	Use of strategies to prepare for and take examinations	Skill
Time Management	Use of time management principles for academic tasks	Self-regulation

Table 2: Sample LASSI items (by scale) and scale reliability

Scale	Sample Item	Coefficient Alpha
Anxiety	I feel very panicky when I take an important test.	.87
Attitude	I do not care about getting a general education; I just want to get a good job.	.77
Concentration	If I get distracted during class, I am able to refocus my attention.	.86
Information Processing	I try to find relationships between what I am learning and what I already know.	.84
Motivation	Even if I am having difficulty in a course, I can motivate myself to complete the work.	.84
Selecting Main Ideas	I have difficulty identifying the important points in my reading.	.89
Self-Testing	To check my understanding of the material in a course, I make up possible test questions and try to answer them.	.84
Study Aids	I try to find a study partner or study group for each of my classes.	.73
Test Taking	I have difficulty adapting my studying to different types of courses.	.80
Time Management	I find it hard to stick to a study schedule.	.85

Theory of Intelligence. The Implicit Theories of Intelligence Scale (Dweck et al., 1995) assesses whether a student endorses an incremental (or growth or malleable) mindset or an entity (fixed) mindset using three reverse-coded items. Responses on a 5-point Likert scale range from 1 = Strongly disagree to 5 = Strongly agree. After reverse coding the items, the responses are averaged to obtain an overall score. Higher values indicate a stronger malleable, or growth mindset. This measure had strong reliability with a Cronbach's alpha of .88. Scale items are included in Table 3.

Table 3: Theory of Intelligence items

Items
You have a certain amount of intelligence and you really can't do much to change it.
Your intelligence is something about you that you can't change very much.
You can learn new things, but you can't really change your basic intelligence.

Demographics. Students completed an online questionnaire outside of class, voluntarily disclosing information about their age, ethnicity/race, socioeconomic status and parental education level. Students provided information on these factors using forced response items (though an optional "other" category was always included). Although some students provided all information, response rates varied for other items. No systematic differences existed between those who chose to answer and those who chose not to answer.

Race/Ethnicity. Students were asked to choose from one of eight categories: African American, Asian, Hispanic, Caucasian, Native American, Arab, and Other.

Given the sample sizes and number of predictor variables used in the regression analyses, it was not feasible to include multiple predictor variables for race/ethnicity. Therefore, the race/ethnicity variable is dichotomously coded 0 if a student self-identifies as Caucasian and 1 if they do not.

Family Income. Table 4 outlines the spread of participants in terms of family income.

Table 4: Family income

	N	% of sample
$0 - $25,000	62	12.2
$25,001 - $50,000	94	18.5
$50,001 - $75,000	67	13.2
$75,001 - $100,000	68	13.4
$100,001 - $125,000	39	7.7
$125,001 - $150,000	40	7.9
$150,001 and above	93	18.3
Not reported	44	8.7
Total	507	100.0

Generation Status. Students were asked to indicate the highest level of education obtained by their mother/legal guardian and their father/legal guardian. Response options included middle school, some high school, high school, some college, associate's degree, bachelor's degree, graduate or professional degree (e.g., MD, MA, JD, PhD), or "I don't know." Guided by previous research demonstrating significant differences between students whose parents had earned an associate's degree and those whose parents had earned a bachelor's degree, students in this study were classified as first generation if the highest response for both mother/legal guardian and father/legal guardian was associate's degree or below. Continuing generation students were those who had at least one parent who had earned a bachelor's degree or above.

Procedure

Data were collected as part of the normal course operations across 22 sections of the coordinated course taught by seven instructors across the four semesters. These 22 sections represent a subset of all sections offered during these four semesters. There are two reasons data for a section were note included: (a) the instructor failed to report the predicted LASSI scores for the semester or (b) the theory of intelligence scale responses were not recorded for the section. The course met three times per week for 50-minute sessions. The course syllabi and all course readings, assignments, and assessments were consistent across the 22 sections and semesters. Course instructors met once per week to discuss upcoming content, strategize teaching methods, and share resources.

On the first class day, students were given an overview of the course and asked to share background information about themselves with their instructor so the instructor could get to know them and support them throughout the semester. Using an online questionnaire outside of class, students voluntarily disclosed information about their age, ethnicity/race, socioeconomic status, and parental education level. Most students completed this questionnaire within one week.

During two consecutive 50-minute class periods, the third and fourth days of class, students completed a series of learning assessments. Although a required component of the course, students did not receive a grade for completing them. Students were told to think of these assessments as an opportunity to learn about their current strategic learning beliefs and behaviors. Instructors encouraged students to answer honestly, noting that honesty now would provide the best information they could use during the semester to become more effective students and that their results would not be made publicly available. These assessments provided concrete information the students and the instructor referred back to throughout the semester, thus helping students focus their efforts on areas they found personally meaningful. The assessments were completed before instruction began.

Students completed the LASSI assessment online during face-to-face instruction time. After a brief introduction to the purpose of the assessment, a general definition for each of the scales, and the logistics of completing the assessment online, students were asked to make hand-written predictions about how well they thought they would do on each scale. Instructors explained that the predictions should be on a 100-point scale, with higher values indicating that they believed themselves to be highly strategic on that particular topic. Students recorded these predictions on two identical forms; they kept one copy and submitted the second form to their instructor.

Once they had hand-recorded their predictions, students went online to respond to each of the 80 statements using a 5-point Likert scale ranging from “Not at all typical of me” to “Somewhat typical of me” to “Very much typical of me.” The items appeared in the same order for each respondent and were presented as 80 statements in a row; they were not organized by scale within the instrument. After all 80 items were completed, the program calculated raw and standardized scores (percentile score equivalents) for each scale and provided these results immediately on screen to the student. The score results document included (for each scale) the raw score, the standardized score, and guidance interpreting the scores. Interpretation guidance indicated that a score of 50% on a particular scale indicated that 50% of the college students participating in the norming sample scored at or below the score they received. The guidance also suggested that scores below the 50th percentile demonstrated a need for improvement, and scores between the 50th and 75th percentiles indicated areas to consider for improvement.

The raw scores and percentile equivalents used in this study were obtained from reporting forms sent to the instructors; the predicted percentile scores were submitted by the students to the instructor at the end of the class period in which the assessment occurred.

The Implicit Theory of Intelligence scale was administered in class as well, but was not completed online. Instead, students recorded their responses to the three-question survey on a Scantron form using a 5-point Likert scale ranging from “Not at all typical of me” to “Somewhat typical of me” to “Very much typical of me.” The instructor processed the Scantron forms after class, and in a later class period, provided students with their individual results.

Instruction during the semester was grounded in the Model of Strategic Learning and organized by individual elements within the skill, will, self-regulation, and academic environment components of the model. All of the LASSI scales were addressed as major topics within the course, supplemented with topics not assessed in the LASSI (such as note-taking). Prior to discussing a topic in class, students were required to read an interactive online text for that topic and come to class prepared to take a brief quiz on what they had read. After taking the quiz, students participated in interactive lectures and in small group activities designed to reinforce the key ideas of the learning and motivational theories supporting that topic.

During the last week of the semester, students again completed the series of learning assessments, including the LASSI and the theory of intelligence scale. The same procedure was followed in administering these post-assessments as was followed when students completed the pre-assessments at the beginning of the semester.

Data Management

Data sets for each course section were created and submitted by the instructor of record for that section. These data sets contained all student-level information analyzed in this study, including responses to the student information survey, pre- and post-assessment data, and all performance (attendance, participation, assignment, quiz, and exam) information. After assigning each participant a study identification number, the individual data sets were combined into one data set for full analysis.

Chapter Four: Results

To explore whether a course designed to help college students become more self-regulating, strategic learners influences the accuracy of students' self-knowledge, I conducted a series of within-subjects ANOVA analyses and regression analyses.

Preliminary Analysis

The overall sample used in this study had 507 students. The majority of the sample was traditional college age (94%); participants had a mean age of 19.8 years and a range of 18 to 38. Students can enroll in this course in either the fall or the spring semester; 43% of participants in this study took the course during a fall semester whereas 57% enrolled in a spring semester. Close to 15% of the sample reported enrolling in this course during their first semester at the University with 27% of students enrolling within their first year. Second year students made up 35% of the sample, third year students accounted for 20% of the sample, and 11% reported being in their fourth year or beyond (only 5 participants reported being beyond 4 years). The most popular colleges or schools represented in the sample are the College of Natural Sciences, the School of Undergraduate Studies, the College of Liberal Arts, and the College of Communication.

The sample was distributed across five racial/ethnic groups: White (34%), Hispanic (25%), Asian (19%), African American (10%), and other (2%, including Native American and Middle Eastern). Reporting ethnicity was voluntary, and there were 55 students who chose not to report their ethnicity.

Students whose highest level of parental education was middle school ($n = 12$), some high school ($n = 21$), high school ($n = 58$), or some college ($n = 77$) were labeled first generation ($n= 168$). First generation students comprised 40% of the sample used for analyses that include generation status. Approximately 93% of the continuing generation students had a parent who had attained a bachelors degree or a graduate or professional degree, indicating that the majority of continuing generation students had at least one parent with personal experience navigating a four-year institution and persisting beyond two years of post-secondary education. Table 5 summarizes information about parental education levels in this sample.

Table 5: Highest level of parental education

		n
First Generation n =190	Middle school	12
	Some high school	21
	High school	58
	Some college	77
	Associate's degree	22
Continuing Generation n = 277	Bachelor's degree	162
	Graduate or professional degree	115
	Not reported	40
	Total	507

Chi-square tests of independence were performed to determine if year in school, semester enrolled in the course, college or school, income, and ethnicity differed by G_1 status. There were no significant differences for year in school (X^2 (5, 474) = 4.90, p = .428), semester enrolled in the course (X^2 (1, 476) = 1.18, p = .277), or college or school (X^2 (11, 475) = 11.40; p = .411). Additionally, there was no difference in course taking in their first semester between G_1 and continuing generation students, X^2 (1, 476) = .270, p = .603. There were significant income differences (X^2 (N, 5) = 101.04; p < .001) with close to 60% of G_1 students reporting family income less than $50,000, and 50% of continuing generation students reporting family income in excess of $100,000. Also, G_1 students were less likely to report being White than were continuing generation students,

X^2 (6, 472) = 60.16; $p < .001$. Because of these relationships, income and ethnicity were included in the regression analyses as control variables.

One-way ANOVA analyses were conducted to determine whether there were mean differences for age or theory of intelligence for G_1 and continuing generation students. No significant relationship between generation status and age or generation status and theory of intelligence was found.

Table 6: One way ANOVA results for age and Theory of Intelligence

	n	M	SD	*df*	*F*	*p*
Age						
G_1	159	19.73	1.84	1	2.11	.147
Continuing	314	20.04	2.89			
TOI						
G_1	120	2.84	1.06	1	.164	.686
Continuing	257	2.80	1.05			

Some of the hypotheses tested in this study require analysis using students' actual score on each of the 10 strategic learning variables as independent variables. Mean actual performance was lowest for the Attitude scale (M = 33.2, SD = 29.6) and was highest for the Motivation scale (M = 47.7, SD = 30.6). Following the practice outlined in Kruger and Dunning (1999), I created an ability variable for each LASSI scale by splitting students into four groups based on their objective performance on that LASSI scale. As shown in Table 7, there was variation across LASSI scales in the cutoff scores for each quartile.

Table 7: Top actual score on each LASSI scale, by quartile

	Bottom Quartile	2nd Quartile	3rd Quartile	Top Quartile
ANX	10	35	70	99
ATT	10	30	50	99
CON	10	30	60	99
INP	15	50	75	99
MOT	20	45	70	99
SFT	10	25	55	99
SMI	15	35	65	99
STA	15	45	75	99
TMT	10	25	60	99
TST	15	40	70	99

Note. ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self Testing; SMI = Selecting Main Ideas; STA = Study Aids; TMT = Time Management; TST = Test Taking

Means and standard deviations for each LASSI scale are shown in Appendix C; an example for Anxiety is shown in Table 8. Without fail across all scores, the bottom quartile had the lowest prediction scores and also had some of the largest standard deviations at the beginning of the semester.

Table 8: Anxiety descriptive statistics for predicted and actual scores

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	142	39.2	23.8	3.9	3.4	42.9	25.3	42.7	26.8
2nd Quartile	117	48.4	23.2	23.5	7.5	49.3	20.1	42.7	26.8
3rd Quartile	134	59.5	19.4	54.8	10.5	63.9	16.2	67.5	22.5
Top Quartile	114	73.7	24.9	86.4	7.0	84.2	17.0	84.6	17.8

Repeated measures ANOVA analyses

To address the research questions about the change in calibration accuracy and bias for each learning factor, I performed mixed ANOVA analyses for each learning factor. For the accuracy analyses, calibration accuracy at the two time points (pre and post) served as the within subjects factor and quartile (bottom, second, third, and top) was used as the between subjects factor. I calculated the dependent variable *accuracy* as the absolute value of the difference between students' predictions and their actual score on the LASSI scale. Scores could range from zero (perfectly accurate) to one hundred (complete lack of accuracy). For example, if a prediction score for a given scale is 60 and the participant's actual performance is 80, the accuracy score for that scale would be 20.

For the bias analyses, calibration bias (initial and final) was the within subjects factor and quartile (bottom, 2^{nd}, 3^{rd}, and top) was the between subjects factor. I calculated the *bias* dependent variable by subtracting students' actual LASSI score from their predicted LASSI score. Positive scores indicate overestimation and negative scores indicate underestimation of performance. For example, if a student predicted she would score in the 80th percentile, but actually scored in the 60th percentile, she would be over estimating capability (+20). In contrast, the student who predicted the 60^{th} percentile and actually scored in the 80^{th} percentile underestimated capability (–20).

The ANOVA design was used as it allows testing of main effects of condition and time as well as of the significance of the interaction between condition and time, all while protecting against inflation of Type 1 error. In order to employ the ANOVA design, the following assumptions must be met: 1) observations are independent within and between cells; 2) the dependent variable is normally distributed within each cell; 3) there is equal population variance within each cell; in repeated measures analyses, an additional assumption of 4) sphericity must be met. As with many experimental studies, the *independence* assumption may have been violated simply due to classroom dynamics influencing student responses. However, participants were instructed to answer pre- and post-assessment items individually, and their scores were not shared publicly with any of their peers. They were encouraged to be truthful in their responses and discouraged from answering in a way that they believed their instructor wanted them to respond. Each student was assigned to one quartile based on his or her actual pre-assessment score. Therefore, the independence assumption did not seem to be violated.

Normality was assessed by examining descriptive statistics and the distribution of scores on the dependent measures in each cell. However, violations of this assumption usually do not inflate the Type 1 error rate, so the F-statistic is said to be robust with respect to this assumption. For each analysis, Mauchly's test (Stevens, 2012) indicated that sphericity had not been violated (as the repeated measures variables only had two levels). Box's M (Stevens, 2012) for each of the analyses indicated that the equality of covariance matrices for the four groups (bottom, second, third, and top quartiles) was violated; however, repeated measures ANOVA is robust to such a violation (Stevens, 2012). Visual inspection of the data, as well as inspecting the ordered standardized residuals, indicated several outlying data points. To determine their impact on study outcomes, a sensitivity analysis was conducted by removing those students whose standardized residuals on the variables of interest were three standard deviations above or below the mean. In all analyses, removing the outliers did not change the overall study results. However, for some scales, removing the outliers did increase effect sizes. Because they did not change the overall findings, the outliers were not removed from the reported analyses.

Regression analyses

Multiple linear regression analysis was employed to help identify the relationship between students' predictions and other student level factors and their actual performance. Model 1 identifies the relationship between predicted score and actual score. Model 2 added demographic characteristics – ethnicity, income, and generation status – to the model. And Model 3 added theory of intelligence. Regression analyses were conducted for each LASSI scale (a) for the overall sample and (b) separately for each quartile (based on actual initial performance for that scale) for both the initial and the final time points.

Linear regression allows us to see the relative contribution of each variable to explaining overall variance and is more descriptive than general analysis of variance procedures (Stevens, 2007). Stevens (2007) cautioned against adding too many predictor variables into the regression equation, but as the sample size is large, the minimum 15:1 sample size to predictor variables ratio suggested was met.

Prior to completing the analysis, regression model assumptions were checked. In order to conduct multivariate regression analyses, error terms must be normally distributed. Non-normally distributed variables – those that are highly skewed or have substantial outliers – can distort relationships or significance tests. Inspection of each variable found that all had a skewness and kurtosis values between -2 and 2. The next assumption is that a linear relationship must exist between the independent and dependent variables. If the relationship between independent and dependent variables is not linear, regression results may underestimate the true relationship, and there is a risk of Type II error for the independent variable. Visual examination of a plot of standardized residuals by standardized predicted values indicated an acceptable level of variance of errors across all levels of the independent variables. Finally, regression analyses require each predicted value to be independent. To address this issue of possible multicollinearity, an analysis of the simple correlations among these predictors was conducted and variance inflation factor (VIF) tests were done, and multicollinaearity was not found to be an issue (Stevens, 2007).

PRIMARY DATA ANALYSIS

I present the primary data analysis results in three sections. In part one, I showcase an example of how the calibration *accuracy* analyses were conducted for one scale (Anxiety). This will include the initial repeated measures ANOVA as well as the second repeated measures ANOVA including generation status as a between-subjects factor. After exploring this one example in depth, I summarize the results from the accuracy analyses for the remaining nine scales. Part two will follow a similar structure, discussing in-depth the calibration *bias* analyses for the Anxiety scale and then summarizing the mean comparison results across all scales. Finally, in part three, I will show the results of the regression analyses done to predict actual scores for all of the scales.

PART 1: CALIBRATION ACCURACY REPEATED MEASURES ANOVA

Anxiety calibration accuracy

A repeated measures ANOVA using Anxiety accuracy at the start of the semester and end of the semester as the within subjects variable and actual performance quartile as the between subjects variable was conducted. Initial and final Anxiety accuracy means and standard deviations by quartile are available in Table 9.

Table 9: Anxiety descriptive statistics for accuracy and bias

	Initial					Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	142	35.2	23.6	35.5	23.1	-0.1	25.9	19.7	16.7
2nd Quartile	117	24.9	24.4	28.7	19.7	-4.3	24.4	19.9	14.6
3rd Quartile	134	4.7	19.5	15.9	12.1	-3.6	22.7	16.7	15.8
Top Quartile	114	-12.8	17.3	15.8	14.6	-0.3	19.4	11.0	16.0

The overall repeated measures ANOVA analysis indicated that mean Anxiety calibration accuracy was different at the beginning of the semester ($M = 24.3$, $SD = 20.0$) and at the end of the semester ($M = 17.0$, $SD = 16.2$); ($F(1, 503) = 46.3$, $p < .001$, *partial* $\eta^2 = .084$) across the sample. Though significant, this effect was weak. As shown in Figure 1, the difference in means between the quartile groups differed across time as well ($F(3, 503) = 12.12$, $p < .001$, *partial* $\eta^2 = .067$), indicating a weak effect size interaction between initial performance and calibration accuracy. Finally, there was an overall accuracy difference between the four performance quartiles (averaging across the two time points) ($F(3, 503) = 37.67$, $p < .001$, *partial* $\eta^2 = .183$). There were 15 outliers whose standardized residuals on either initial or final accuracy were greater than 3. Removing these outliers did not impact the assumptions for the analysis, nor did removing them change the test outcome. Removing the outlying data points resulted in improved effect sizes: from 0.084 to 0.124, from 0.067 to 0.073, and from 0.183 to 0.227. These data points were not removed for the remainder of the Anxiety calibration accuracy analyses.

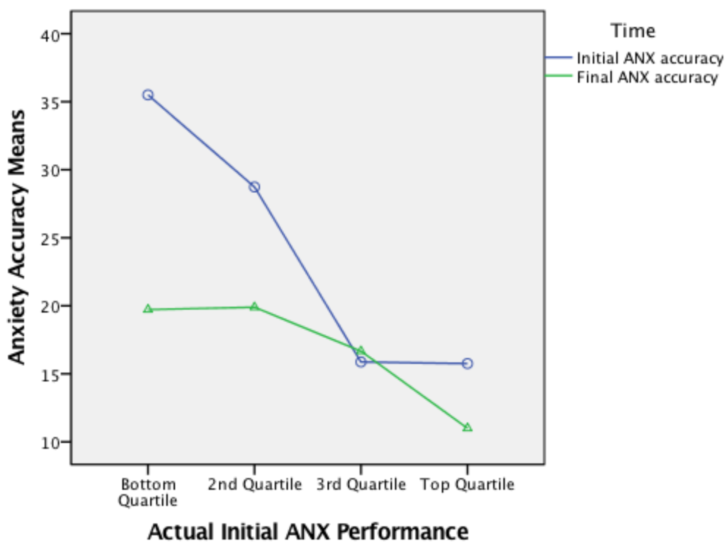


Figure 1: Initial and final Anxiety accuracy means by quartile

Follow up t-tests were conducted to assess mean level change in calibration accuracy across the four performance groups. The t-tests indicated that at the beginning of the semester, students in the bottom quartile (n = 142; M = 35.5) differed in their accuracy as compared to students in the top quartile (n = 114; M = 15.8; $t = 7.92$, $p < .001$, two-tailed). These two groups also differed at the end of the semester ($t = 4.23$ $p < .001$, two-tailed). Table 10 shows the results of the t-tests comparing the bottom and top quartiles; Appendix G contains similar tables for the remainder of the Anxiety comparisons. Of note in the additional t-tests: students in the top two quartiles did not differ in their accuracy assessments initially, but at the end of their semester, their accuracy was significantly different from each other ($t = 2.80$, $p = 0.005$, two-tailed). The mean accuracy score for the third quartile became slightly worse (moving from a difference of 15.9 initially to 16.7 at the end of the semester), whereas the top quartile became more accurate (moving from an initial difference of 15.8 to 11.0 at the end of the semester). The t-tests also show that the bottom and 2nd quartiles differed in their accuracy at the start of the semester, but at the end, there was no statistically significant difference. This pattern held for comparisons between the 2nd and 3rd quartile as well.

Table 10: Anxiety accuracy t-test comparing for the lowest and highest quartiles

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Bottom Quartile	142	35.5	23.2	7.92	0.000
	Top Quartile	114	15.8	14.6		
Final Anxiety Accuracy	Bottom Quartile	142	19.7	16.7	4.23	0.000
	Top Quartile	114	11.0	16.0		

A second repeated measures ANOVA was conducted, this time to include generation status as a second between-subjects variable. There were four levels of actual ability (the Anxiety performance quartiles) and two levels of generation status: continuing generation and first generation (G_1). There were some students who chose not to disclose their parent's highest level of education. These students were excluded from these analyses, thus the sample size for used for this repeated measures ANOVA is n = 476. Table 11 shows the distribution of G_1 and continuing generation students across the quartiles. For Anxiety, approximately 67% of the G_1 students placed into the bottom two quartiles as compared to 47% of the continuing generation students. As placement into quartiles was done using actual LASSI scores, the higher proportion of G_1 students in these lower two quartiles indicated that G_1 students did not cope with Anxiety as well as their continuing generation peers.

Table 11: Distribution of continuing and first generation students in each Anxiety quartile

	Continuing Generation	G_1	*Total*
Bottom Quartile	82 *(25.9%)*	54 *(39.7%)*	136
2nd Quartile	67 *(21.1%)*	43 *(27.0%)*	110
3rd Quartile	90 *(28.4%)*	34 *(21.4%)*	124
Top Quartile	78 *(24.6%)*	28 *(17.6%)*	106
Total	317 *(100%)*	159 *(100%)*	476

The overall repeated measures ANOVA results indicated significant main effects of time and quartile at the .05 significance level. The significant main effect of time ($F(1, 468) = 44.69$, $p < .001$, partial $\eta^2 = .087$) tells us that mean Anxiety accuracy was different at the beginning of the semester ($M = 24.29$ $SD = 20.14$) and at the end of the semester ($M = 16.70$ $SD = 15.74$). Though significant, this effect was weak. Post hoc t-tests showed that Anxiety accuracy at the beginning of the semester did not differ for the lower two quartiles or the top two quartiles, but all other comparisons did differ. As this study is exploratory, these post hoc tests did not use a correction for type I error. The main effect of quartile tells us that accuracy was not consistent across the four groups ($F(3, 468) = 36.03$, $p < .001$, *partial* $\eta^2 = .188$).

The main effect of generation status was not significant ($F(1, 468) = 1.49$, $p = .222$, *partial* $\eta^2 = .003$). Nor was the quartile group x generation status interaction (F(3,

468) = 1.22, p = .301, *partial* η^2 = .008). The time x generation status interaction was not significant as well (F(1, 468) = 0.273, p = .601, *partial* η^2 = .001).

However, there was a significant three-way interaction of time x anxiety quartile x generation status (F(3, 468) = 3.51, p = .015, *partial* η^2 = .022). There were 14 outliers whose standardized residuals for either initial or final accuracy were greater than or equal to 3. Just as in the first repeated measures ANOVA, removing these outliers did not impact the assumptions for the analysis, nor did removing them change the test outcomes. The main effects of time and quartile were still significant, as was the time x quartile interaction and the time x quartile x generation status interaction. Removing the outlying data points resulted in improved effect sizes for the significant outcomes. The effect size for time increased from 0.087 to 0.115. The effect size for quartile increased from 0.188 to 0.215. The effect size for the time x quartile interaction improved from 0.040 to 0.042. Finally, the effect size for the time x quartile x generation status interaction improved from 0.022 to 0.028. These data points were not removed for the remainder of the Anxiety calibration accuracy analyses.

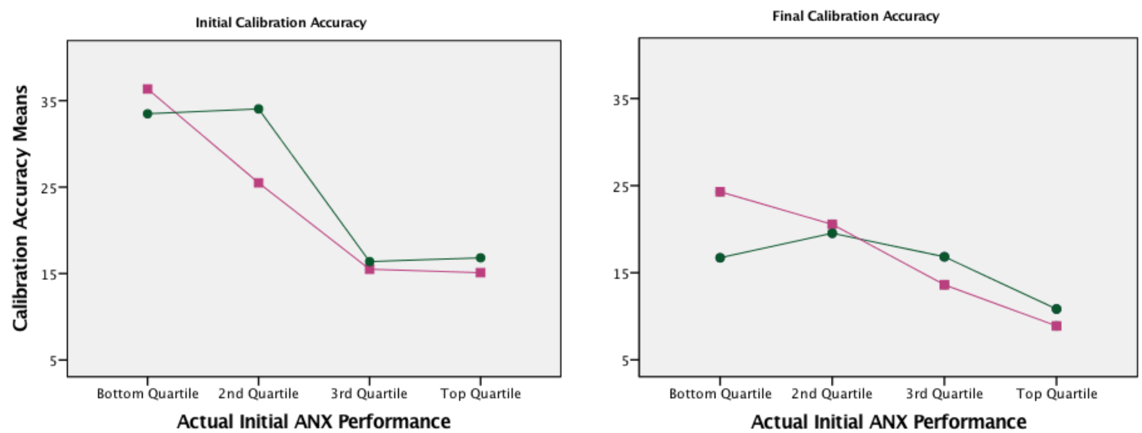
Following the significant three-way interaction between time, actual level of Anxiety performance, and generation status, I completed a mixed ANOVA to determine if first and continuing generation students differed from each other at the start of the semester and at the end of the semester. This analysis showed a significant effect of time (F(1, 474) = 45.16, p < .001, *partial* η^2 = .087), no significant interaction for time and generation status (F(1, 474) = .554, p = .457 *partial* η^2 = .001), and a significant main effect of generation status (F(1, 474) = 6.30, p = .012, *partial* η^2 = .013).

To understand the main effect of time, follow-up t-tests were conducted collapsing students into two groups: continuing generation and G_1. The results indicated that continuing generation (n = 317; $M_{initial}$ = 22.9, M_{final} = 15.9) and G_1 (n = 159; $M_{initial}$ =

27.0, M_{final} = 18.3) students differed in accuracy at the beginning of the semester (t = -2.12, p = .034, two-tailed) but not at the end of the semester (t = -1.51, p = .133, two-tailed).

To investigate further the main effect of generation status, follow-up t-tests were conducted comparing continuing and G_1 students. These t-tests indicated that at the start of the semester, G_1 students in the bottom quartile (n = 54; M = 36.4) did not differ from continuing generation students in the bottom quartile (n = 82; M = 33.5; t = .708, p = .470, two-tailed). At the end of the semester, however, there was a significant difference between G_1 students (M = 16.7) and continuing generation students (M = 24.3) in the bottom quartile (t = -2.644, p = .009, two-tailed). Continuing generation and G_1 students improved their Anxiety accuracy, but continuing students showed greater accuracy improvement than their G_1 peers.

A different pattern was found for students in the 2nd quartile. Instead of starting off the same and ending different, in the 2nd quartile G_1 students (n = 43; $M_{initial}$ = 34.1, M_{final} = 20.6) and continuing generation students (n = 67; $M_{initial}$ = 34.1, M_{final} = 19.5) initially differed in terms of Anxiety accuracy (t = -2.230, p = .028, two-tailed), but did not differ in accuracy at the end of the semester (t = -.346, p = .730, two-tailed). No differences between G_1 and continuing generation students were found in the 3rd and top quartiles. These patterns can be seen in Figure 2, which shows both initial and final Anxiety accuracy means for G_1 and continuing generation students by quartile.



Generation Status: Continuing Generation First Generation

Figure 2: Comparison of initial and final Anxiety accuracy means for G_1 and continuing generation students, by quartile

Calibration accuracy results summary for all LASSI scales

The tests of within-subjects effects (using only quartile as the between-subjects factor) indicated statistically significant group differences in initial calibration accuracy and final calibration accuracy for all ten LASSI learning factors. These results are summarized in Appendix E. The difference in means between the quartile groups differed across time, indicating interactions between initial performance (quartile) and time. The strength of the interaction effect varied across learning factors, with the weakest effect found for the interaction between time and quartile for Anxiety (*partial* $\eta^2 = 0.067$) and the strongest effect found for the interaction between time and quartile for Attitude accuracy (*partial* $\eta^2 = 0.259$).

Follow-up t-tests for the initial repeated measures ANOVA using $p = .05$ (not an adjusted p-value) indicated that for all 10 scales, the top and bottom quartiles significantly differed in accuracy at the beginning of the semester and at the end of the semester.

Table 12: Accuracy t-test results for all scales by comparison groups

	Differ Initial Differ Final	Differ Initial Not Sig Final	Not Sig Initial Not Sig Final	Not Sig Initial Differ Final
Bottom vs. Top	INP, SMI, TST ANX, ATT, MOT CON, SFT, STA, TMT			
Bottom vs. 2nd	INP	SMI, TST ANX, MOT CON, SFT, STA	ATT TMT	
2nd vs. 3rd	INP, SMI STA	TST ANX, ATT, MOT CON, SFT, TMT		
3rd vs. Top	SMI ATT, MOT CON, TMT			INP, TST ANX SFT, STA

Note: ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self-Testing; SMI = Selecting Main Ideas; STA = Study Aids; TST = Test Taking; TMT = Time Management; Color indicates Model of Strategic Learning component: Skill, Will, or Self Regulation

Table 12 summarizes the patterns that emerged from analyzing accuracy differences between quartiles with the t-test comparisons. For many scales (Anxiety, Concentration, Motivation, Selecting Main Ideas, Self Testing, Study Aids, and Test Taking), the *bottom and second quartiles* (representing the bottom half of students in the sample) differed at the beginning of the semester, but not at the end of the semester. Attitude and Time Management did not differ at the beginning, nor at the end for the bottom two quartiles. Information Processing was the only scale for which the bottom and second quartiles differed at both time points.

Comparisons between the third and top quartiles (representing the top half of the sample) indicated that these groups did not differ on accuracy at the beginning of the semester but did differ in accuracy at the end of the semester for half of the scales: Anxiety, Information Processing, Self Testing, Study Aids, and Test Taking. On the other half of the scales (Attitude, Concentration, Motivation, Selecting Main Ideas, and Time Management), accuracy differed at both the beginning *and* at the end of the semester.

In the middle of the sample (comparing the second and third quartiles), accuracy differed at the beginning of the semester but not at the end for Anxiety, Attitude, Concentration, Motivation, Self Testing, Test Taking, and Time Management. Accuracy differed at both the beginning and at the end of the semester for Information Processing, Selecting Main Ideas, and Study Aids.

Including generation status

The distribution of G_1 students into the bottom two quartiles was not consistent across all scales. Only the distribution across Motivation quartiles mimicked the contrast in proportion of G_1 and continuing generation students seen in the Anxiety distribution, with 60% of the G_1 students in this sample scoring in the bottom two quartiles compared to 44% of the continuing generation students. A higher proportion of continuing generation students placed into the *top* two quartiles for every scale.

As with the first repeated measures ANOVA, for all LASSI scales, there were significant main effects of time and quartile and a significant interaction of time x quartile. There was no main effect of generation status for any of the scales. For three scales – Anxiety, Motivation, and Selecting Main Ideas – there was a significant three-way interaction for time x quartile x generation status at a $p < .05$ level. The time x quartile x generation status interaction was not significant for Attitude at $p = .05$, but was significant at a $p < .10$ level. Anxiety, Attitude, and Motivation comprise the Will variables, so significant interactions including generation on all of the Will variables is an interesting finding. Especially contrasted with no significant interactions containing generation status for any of the self-regulation variables.

Following up on the significant three-way interaction between time, actual level of performance, and generation status for Motivation and Selecting Main Ideas, I completed a mixed ANOVA to determine if first and continuing generation students differed from each other at the start of the semester and at the end of the semester. For Selecting Main Ideas, this analysis showed a significant effect of time (F(1, 474) = 93.74, $p < .001$, *partial* $\eta^2 = .165$), but no significant interaction for time and generation status (F(1, 474) = 0.941, $p = .333$, *partial* $\eta^2 = .002$), and no significant main effect of generation status (F(1, 474) = 0.038, $p = .846$, *partial* $\eta^2 = .000$). As these follow-up t-tests are similar to the ones done for the first repeated measures ANOVA analysis for accuracy (reported above), they are not repeated here.

For Motivation, the mixed ANOVA for first and continuing generation students analysis showed a significant effect of time (F(1, 474) = 80.1, $p < .001$, *partial* $\eta^2 =$ .145), a significant interaction for time and generation status (F(1, 474) = 11.6, $p = .001$ *partial* $\eta^2 = .024$), and no significant main effect of generation status (F(1, 474) = 2.7 $p =$ .091, *partial* $\eta^2 = .006$). To understand the main effect of time for Motivation, follow-up t-tests were conducted collapsing students into two groups: continuing generation and G_1. The results indicated that continuing generation ($n = 317$; $M_{initial} = 24.2$, $M_{final} = 17.9$) and G_1 ($n = 159$; $M_{initial} = 30.2$, $M_{final} = 16.3$) students differed in accuracy at the beginning of the semester ($t = -3.06$, $p = .002$, two-tailed) but not at the end of the semester ($t = 1.069$, $p = .286$, two-tailed).

Further analysis of the main effect of generation status for Motivation used follow-up t-tests to compare continuing and G_1 students. These t-tests indicate that at the start of the semester, G_1 students in the bottom quartile differed from continuing generation students in the bottom quartile. At the end of the semester, however, there was no significant difference between G_1 students and continuing generation students in the bottom quartile. This is opposite the Anxiety pattern for the lowest quartile. Continuing generation students improved their Motivation accuracy, while G_1 students Motivation accuracy decreased. A different pattern was found for students in the 2nd and 3rd quartiles. Instead of starting off the different and ending the same, in the 2nd and 3rd quartiles G_1 students and continuing generation students initially differed in terms of Motivation accuracy, but did not differ in accuracy at the end of the semester. No differences between G_1 and continuing generation students were found in the top quartile.

PART 2: CALIBRATION BIAS REPEATED MEASURES ANOVA

Anxiety calibration bias

A repeated measures ANOVA using anxiety bias at the start of the semester and end of the semester as the within subjects variable and actual performance quartile as the between subjects variable was conducted. Initial and final Anxiety bias means and standard deviations by quartile are available in Table 9.

The overall repeated measures ANOVA analysis indicated that mean Anxiety bias was different at the beginning of the semester (M = 14.0, SD = 28.2) and at the end of the semester (M = -2.0, SD = 23.4); ($F(1, 503) = 121.47$, $p < .001$, *partial* $\eta^2 = .195$) across the sample. The difference in means between the quartile groups differed across time as well ($F(3, 503) = 61.41$, $p < .001$, *partial* $\eta^2 = .268$), indicating a moderate effect size interaction between initial performance and calibration bias. Finally, there was an overall bias difference between the four performance quartiles (averaging across the two time points) ($F(3, 503) = 53.54$, $p < .001$, *partial* $\eta^2 = .242$).

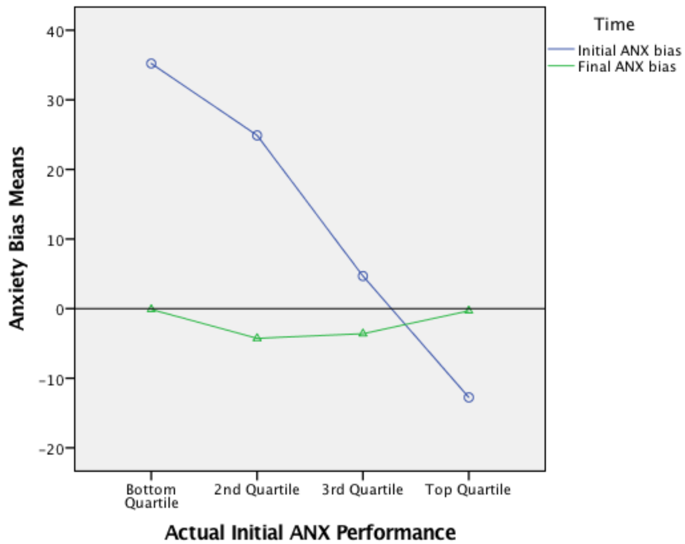


Figure 3: Anxiety bias means by quartile

There were 8 outliers whose standardized residuals on either initial or final bias were greater than 3. Removing these outliers did not impact the assumptions for the analysis, nor did removing them change the test outcome, but effect sizes were improved from 0.195 to 0.226 from 0.268 to 0.278, and from 0.242 to 0.258. The outliers were retained for the remainder of the analyses. Follow up t-tests were conducted to assess mean level change in calibration bias across the four performance groups. Table 13 shows the results of the t-tests comparing the bottom and top quartiles; Appendix I contains similar tables for the remainder of the Anxiety comparisons.

Table 13: Anxiety bias t-test comparing for the lowest and highest quartiles

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Bottom Quartile	142	35.2	23.6	18.75	0.000
	Top Quartile	114	-12.8	17.3		
Final Anxiety Bias	Bottom Quartile	142	-.11	25.9	0.072	0.945
	Top Quartile	114	-.32	19.4		

T-test comparisons indicated that, in terms of their Anxiety bias, all groups significantly differed from each other at the start of the semester. By the end of the semester, however, no significant differences in bias were found between any of the quartiles. For example, at the beginning of the semester, students in the bottom quartile differed in their bias as compared to students in the top quartile ($t = 18.75$, $p < 0.001$). By the end of the semester, this difference was no longer significant ($t = 0.072$; $p = 0.945$). Students in the bottom quartile moved from greatly overestimating their ability to cope with Anxiety ($M = 35.2$) to slightly underestimating ($M = -0.11$), whereas students in the top quartile underestimated their capabilities less at the end of the semester ($M = -0.32$) than at the beginning ($M = -12.8$). At the beginning of the semester, the top quartile was the only group to underestimate their ability to cope with Anxiety. By the end of the semester, all groups were ever so slightly under estimating their ability to cope.

A second repeated measures ANOVA for bias was conducted, and like the accuracy analyses, this time generation status was included as a second between-subjects variable. As explained above, the sample size used for this repeated measures ANOVA is $n = 476$, and Table 10 shows the distribution of G_1 and continuing generation students across the quartiles.

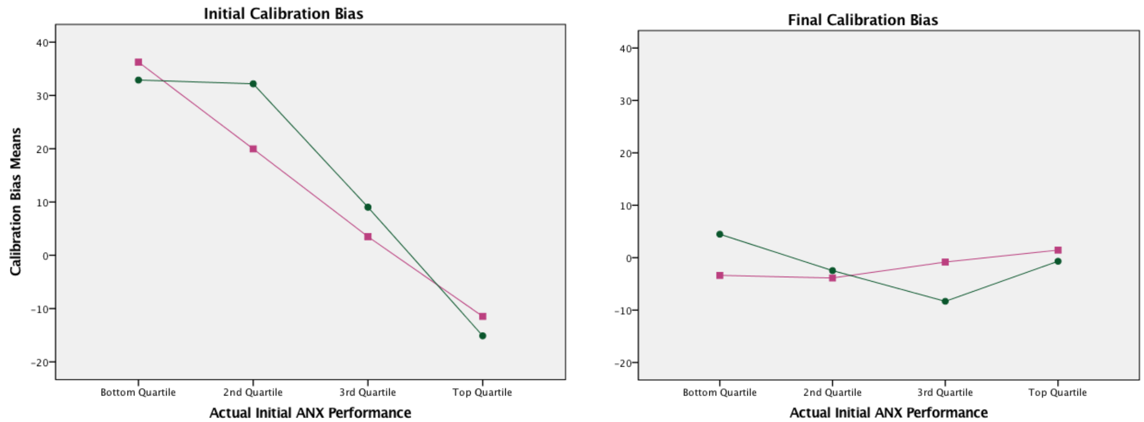
The overall repeated measures ANOVA results indicate significant main effects of time and quartile at the .05 significance level. The significant main effect of time ($F(1, 468) = 101.62$ $p < .001$, *partial* $\eta^2 = .178$) tells us that average Anxiety bias was different at the beginning of the semester ($M = 24.3$ $SD = 20.1$) and at the end of the semester ($M = 16.7$ $SD = 15.7$). Bonferroni corrected post hoc tests showed that Anxiety bias at the beginning of the semester and at the end of the semester differed across all quartiles. The main effect of quartile tells us that bias was not consistent across the four groups ($F(3, 468) = 44.51$, $p < .001$, *partial* $\eta^2 = .222$).

The main effect of generation status was not significant ($F(1, 468) = 0.646$, $p = .422$, *partial* $\eta^2 = .001$). Nor was the quartile group x generation status interaction ($F(3, 468) = 1.647$, $p = .178$, *partial* $\eta^2 = .010$). The time x generation status interaction effect was not significant as well ($F(1, 468) = 0.855$, $p = .356$, *partial* $\eta^2 = .002$).

However, there was a significant three-way interaction of time x anxiety quartile x generation status ($F(3, 468) = 4.022$, $p = .008$, *partial* $\eta^2 = .025$). There were 10 outliers whose standardized residuals for either initial or final bias were greater than or equal to 3. Just as in the first bias repeated measures ANOVA, removing these outliers did not impact the assumptions for the analysis, nor did removing them change the test outcomes. The main effects of time and quartile were still significant, as was the time x quartile interaction and the time x quartile x generation status interaction. Removing the outlying data points resulted in improved effect sizes for the significant outcomes. The effect size for time increased from 0.178 to 0.204. The effect size for quartile increased from 0.222 to 0.255. The effect size for the time x quartile interaction improved from 0.240 to 0.243. Finally, the effect size for the time x quartile x generation status interaction improved from 0.025 to 0.030. These data points were not removed for the remainder of the Anxiety calibration bias analyses.

Following the significant three-way interaction between time, actual level of Anxiety performance, and generation status, I completed a mixed ANOVA to determine if first and continuing generation students' calibration bias differed at the start of the semester and at the end of the semester. This analysis showed a significant effect of time ($F(1, 474) = 94.44$, $p < .001$, *partial* $\eta^2 = .166$), a significant main effect of generation status ($F(1, 474) = 4.865$, $p = .028$, *partial* $\eta^2 = .010$), and a significant interaction for time and generation status ($F(1, 474) = 3.94$, $p = .048$ *partial* $\eta^2 = .001$). T-tests contrasting continuing generation and G_1 students at each time point indicated that continuing generation students ($n = 317$; $M_{initial} = 11.8$, $M_{final} = -1.6$) and G_1 ($n = 159$; $M_{initial} = 19.1$, $M_{final} = -1.0$) differed in bias at the beginning of the semester ($t = -2.71$, $p = .007$, two-tailed) but not at the end of the semester ($t = -.236$, $p = .813$, two-tailed).

Additional follow-up t-tests were conducted comparing continuing and G_1 students in each quartile. These t-tests indicate that at the start of the semester, G_1 students and continuing generation students in the bottom, 3rd, and top quartiles did not differ from each other. The 2nd quartile was the only group that followed a different pattern. At the beginning of the semester, continuing and G_1 groups in the 2nd quartile differed on Anxiety bias ($t = -2.57$; $p = 0.011$); G_1 students were much more positively biased ($M = 32.19$) than their continuing generation peers ($M = 19.97$). At the end of the semester, however, no significant difference existed between these groups ($t = -.289$; $p = .773$) and, on average, the groups were slightly negatively biased ($M = -2.4$ and $M = -3.9$). These patterns can be seen in Figure 2, which shows both initial and final Anxiety accuracy means for G_1 and continuing generation students by quartile.



Generation Status: ____ Continuing Generation ____ First Generation

Figure 3: Anxiety bias means for G_1 and continuing generation students, by quartile

Calibration bias results summary for all LASSI scales

The tests of within-subjects effects (using only quartile as the between-subjects factor) indicated statistically significant group differences in initial calibration bias and final calibration bias for all ten LASSI learning factors. These results are summarized in Appendix H. Significant interaction effects for time x quartile were seen for each scale as well. The strength of the interaction effect varied across learning factors, with the strongest effects found for the Skill variables: Information Processing (*partial* η^2 = 0.349), Selecting Main Ideas (*partial* η^2 = 0.366), and Test Taking (*partial* η^2 = 0.363). Interaction effect sizes on the Will and Self Regulation variables ranged from *partial* η^2 = 0.200 (Concentration) to *partial* η^2 = 0.329 (Study Aids).

Follow-up t-tests for the initial repeated measures ANOVA using p = .05 indicated that, generally, groups differed significantly at the beginning of the semester, but not at the end of the semester. Table 13 provides more detail about bias patterns for selected quartile comparisons. For eight scales, the top and bottom quartiles significantly differed in bias at the beginning of the semester and at the end of the semester. For two scales, Attitude and Time Management, these quartiles significantly differed at the beginning and end of the semester.

Table 14: Bias t-test results for all scales by comparison groups

	Differ Initial Differ Final	Differ Initial Not Sig. Final	Not Sig Initial Not Sig Final	Not Sig Initial Differ Final
Bottom vs. Top	ATT TMT	INP, SMI, TST ANX, MOT CON, SFT, STA		
Bottom vs. 2nd		INP, SMI, TST ANX, MOT CON, SFT, STA	ATT TMT	
2nd vs. 3rd		INP, SMI, TST ANX, ATT, MOT CON, SFT, STA, TMT		
3rd vs. Top	SMI	INP, TST ANX, ATT, MOT CON, SFT, STA, TMT		

Note: ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self-Testing; SMI = Selecting Main Ideas; STA = Study Aids; TST = Test Taking; TMT = Time Management; Color indicates Model of Strategic Learning component: Skill, Will, or Self Regulation

For all scales, the lowest quartile showed significant improvement in bias; all became less negatively bias (overestimated less) from the beginning to the end of the semester. This shift from extreme over estimation to slight overestimation/under estimation is especially impressive for the Will variables: Anxiety ($M_{initial}$ = 35.2, M_{final} = -0.3), Attitude ($M_{initial}$ = 57.7, M_{final} = 15.2), and Motivation ($M_{initial}$ = 44.7, M_{final} = 0.2).

The top quartile results were not as consistent. On average, students in the top quartile underestimated their capability at both the beginning and end of the semester, becoming less negatively biased from beginning to end for the majority of scales: Anxiety, Information Processing, Motivation, Selecting Main Ideas, Self-testing, Test Taking, and Time Management. The Attitude scale was the only scale for which top quartile students were initially significantly ($t = 7.366$, $p < 0.001$) positively biased (overestimating capabilities); they remained significantly ($t = 4.33$, p < 0.001) positively biased at the end of the semester but to a lesser degree ($M_{initial} = 9.9$, $M_{final} = 8.6$).

Including generation status

As with the first calibration bias repeated measures ANOVA, for all LASSI scales, there were significant main effects of time and quartile and a significant time x quartile interaction. The time x generation interaction was significant for two scales, Motivation and Time Management. There was no main effect of generation status nor was there a significant interaction of quartile x generation for any of the scales.

For two scales – Anxiety and Time Management – there was a significant three-way interaction for time x quartile x generation status at a $p < .05$ level. The follow-up tests for Anxiety are described above; here, I outline the results of follow up t-tests for Time Management. T-tests indicated that in three quartiles – bottom, second, and top - continuing generation and G_1 groups did not differ significantly at either the beginning or end of the semester. No significant difference in bias for G_1 and continuing generation groups in the 3rd quartile at the start of the semester, but at the end, there was a significant difference in bias ($t = 2.87$; $p = 0.005$). Continuing generation students became less positively bias ($M_{initial} = 14.4$, $M_{final} = 3.0$) whereas G_1 students moved from being positively biased ($M_{initial} = 19.0$) to negatively biased ($M_{final} = -8.9$).

Part 3: Regression analyses

Regression analyses were used to address Research Questions 2 and 3, which examined the effect of generation status and theory of intelligence on student calibration. Three regression models were tested. Model 1 established the relationship between student predictions and actual scores. Model 2 added demographic characteristics – ethnicity, income, and generation status. Model 3 added theory of intelligence. Regression model 3 is summarized by the following equation: $Y_{PREDICTED}$ = intercept + $b_1X_{self\text{-}assessment} + b_2X_{generation\ status} + b_3X_{income} + b_4X_{ethnicity} + b_5X_{theory\ of\ intelligence}$. $Y_{PREDICTED}$ represents the outcome measure (actual score for each LASSI scale) being regressed onto the predictors (self-assessment, demographic variables, and theory of intelligence) weighted with a constant value. These three models were tested at both the beginning and the end of the semester for (a) each LASSI scale using the overall sample and (b) each LASSI scale, quartile-by-quartile. The following discussion captures the analysis of results I completed for each of these regressions.

Overall initial Anxiety regression

Model 1 examining the main effect of prediction on actual score explained 31% of the initial Anxiety scores (R^2 = .31, F (1, 357) = 161.46, $p \leq .001$). In this model, initial Anxiety prediction was a significant predictor of initial actual Anxiety scores (β = .558, $p \leq .001$). Model 2 expanded to include generation status, income, and ethnicity. Comparison groups for these three variables were (a) students whose highest parental educational level as associates degree and below, (b) students with family income below $75,000, and (c) Caucasian students. A comparison of R^2 between the two models indicated that Model 2 improved the model; the model now explained 35.3% of the variance in actual initial Anxiety (R^2 = 35.3, F(4, 354) = 48.23, $p \leq .001$). In this model, prediction scores remained a strong and significant predictor of actual Anxiety

(β = .551, p < .001), and two additional significant predictors emerge. Increasing parental education from an Associate's degree (or below) to a bachelor's degree or above was associated with a positive increase in actual scores (β = .110, p = .025), and minority status was associated with a decrease in actual scores (β = -.116, p = .013). Model 3 included student's theory of intelligence scores. A comparison of R^2 between Model 2 and Model 3 indicated that Model 3 did not improve the model fit (ΔR^2 = .000, p = .751).

Table 15: Regression examining initial Anxiety actual score

Model		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	Δ R^2
1	(Constant)	3.36			
	Prediction	0.06	.558***	.311	
2	(Constant)	4.49			.041***
	Prediction	0.06	.547***	.353	
	Generation Status	3.25	.110*		
	Income	3.27	.039		
	Ethnicity	3.09	-.116*		
3	(Constant)	5.64		.353	.000
	Prediction	0.06	.551***		
	Generation Status	3.25	.110*		
	Income	3.27	.039		
	Ethnicity	3.10	-.117*		
	Theory of Intelligence	1.32	.003		

Note. *p < .05. **p < .01. ***$p \leq$ .001.

These three models were tested again at the end of the semester using the predictions and actual scores gathered during the final weeks of class. Model 1 continued to be significant, explaining 39% of the end-of-semester Anxiety scores (R^2 = .393, F(1, 356) = 231.95, $p \leq$ .001), with final Anxiety prediction a significant predictor of actual Anxiety scores (β = .627, $p \leq$ .001). This time, however, Model 2, which included generation status, income, and ethnicity, did not improve the model (ΔR^2 = .000, p =

.668). Whereas generation status and ethnicity were significant predictors of actual Anxiety scores at the beginning of the semester, at the end of the semester they no longer explained a significant portion of the variance in actual Anxiety scores.

Table 16: Regression examining final Anxiety actual score

Model		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.11			
	Prediction	0.05	.628***	.393	
2	(Constant)	4.12			.003
	Prediction	0.05	.631***	.390	
	Generation Status	2.78	.035		
	Income	2.79	-.056		
	Ethnicity	2.65	-.023		
3	(Constant)	5.02		.389	.000
	Prediction	0.05	.630***		
	Generation Status	2.79	.035		
	Income	2.79	-.055		
	Ethnicity	2.66	-.023		
	Theory of Intelligence	1.14	.010		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

Anxiety quartile analysis

Another set of regressions for the beginning and the end of the semester data was run, this time for each performance quartile. Table 17 displays the quartile regression outcomes for Anxiety. At the beginning of the semester, student predictions did not significantly predict actual initial score for students in the bottom two quartiles. At the end of the semester, however, Model 1, which contains only student predicted scores, significantly predicted actual final Anxiety scores for all quartiles at a $p \leq .001$. Predictions accounted for between 19% and 22% of the variance in final actual Anxiety scores. Income, ethnicity, generation status, and theory of intelligence were not significant predictors for any of the individual quartiles at either the beginning or at the end of the semester, despite ethnicity and generation status emerging as significant predictors at the beginning of the semester in the whole-sample analysis.

Table 17: Regression outcomes by quartile for Anxiety

	Initial	ΔR^2 significance	Final	ΔR^2 significance
Bottom Quartile *n* = 102				
Model 1	Not sig		$R^2 = .214$	
Model 2	Not sig		$R^2 = .243$	0.303
Model 3	Not sig		$R^2 = .393$	0.642
2nd Quartile *n* = 80				
Model 1	Not sig		$R^2 = .215$	
Model 2	Not sig		$R^2 = .230$	0.692
Model 3	Not sig		$R^2 = .231$	0.748
3rd Quartile *n* = 89				
Model 1	$R^2 = .092$		$R^2 = .219$	
Model 2	$R^2 = .131$	0.292	$R^2 = .276$	0.095
Model 3	$R^2 = .133$	0.653	$R^2 = .276$	0.943
Top Quartile *n* = 88				
Model 1	$R^2 = .153$		$R^2 = .190$	
Model 2	$R^2 = .168$	0.679	$R^2 = .204$	0.676
Model 3	$R^2 = .172$	0.530	$R^2 = .204$	0.897

Regression analyses summary, overall regressions

Appendix J contains the initial and final models summarized here. At the beginning of the semester, all learning factors had models that significantly predicted actual score. The Information Processing model explained the least amount of variance in final score (18.1%); in this model, prediction, generation status, income, and ethnicity were all significant predictors. Information Processing, along with the other two Skill factors, Test Taking (21.1%) and Selecting Main Ideas (20.9%) made up the lowest three prediction models at the start of the semester. Test Taking continued to be one of the least predictive models at the end of the semester (explaining 24.0% of the variance in actual final score). The model predicting actual Concentration score explained the most amount of variance at the beginning of the semester (24.0%). And, although the Concentration model continued to predict a large amount of variance at the end of the semester (40.0%), a different Self-Regulation factor model - Time Management - captured the most amount of variance (43.5%) across all models for all factors.

Race/ethnicity was a significant predictor at the beginning of the semester for the most significant Test Taking (β = -.155), Information Processing (β = -.168), Attitude (β = -.105), Anxiety (β = -.116), Motivation (β = -.104) and Self Testing (β = -.120) models. It is worth noting that all three Will variables are listed here. Race/ethnicity did not appear as a significant predictor in *any* of the models at the end of the semester. In each of these models, minority status was associated with a decrease in actual scores on the learning factor.

Income did not appear as a significant predictor in many models; it was a significant predictor for two Skill factors – Test Taking (β = .125) and Information Processing (β = -.165) – at the start of the semester and one Self-Regulation factor – Time Management (β = -.131)– at the end of the semester. For Test Taking, increasing family income from under $75,000 to over $75,000 was associated with increased actual Test Taking scores. Increasing income was associated with decreases in Information Processing and Time Management scores.

At the start of the semester, generation status was a significant predictor in the most explanatory models for the Information Processing models (β = .151), Anxiety (β = .110), Motivation (β = .165), and Study Aids (β = .158). At the end of the semester, it was not a significant predictor in any of the overall models. Higher parental education was associated with higher actual scores on these four factors.

Theory of intelligence was a significant predictor in initial models for Test Taking (β = .106, Attitude (β = .254), Motivation (β = .131), and Study Aids (β = .130). At the end of the semester, the only one of the four models no longer significantly influenced by theory of intelligence was the Study Aids model. A more malleable mindset continues to be associated with higher actual scores for Test Taking (β = .108), Attitude (β = .016), and Motivation (β = .122).

Regression analyses summary, by quartile

Bottom quartile

At the start of the semester there were five models that significantly predicted actual scores for the bottom quartile students: Test Taking (Skill), Selecting Main Ideas (Skill), Motivation (Will), Study Aids (Self Regulation), and Concentration (Self Regulation). Ethnicity was a significant predictor in two models (Test Taking and Study Aids) and theory of intelligence was significant in one model (Concentration). Income and generation status were not significant predictors in any model. By the end of the semester, no significant model had these factors as significant predictors. At the end of the semester, the model that explained the most variance in actual scores was for the Concentration factor (28.6% of the variance explained by the model, which included only student predictions). The largest improvement in explanation occurred with the Time Management factor; this factor did not have a significant model at the start of the semester, but finished with a model that accounted for 21.7% of the variance in actual scores. Time Management had some of the largest gains in each of the four quartiles, with all end of semester models predicting at least 20% of actual scores.

Overall, the largest improvements in the bottom quartile came about in self-regulation factors. In addition to Time Management as explained above, Self Testing moved from being non significant to explaining 18.7% of the variance in actual scores, Study Aids went from explaining 9.8% to explaining 23.5%, and Concentration moved from explaining 9.3% of the variance at the start of the semester to explaining 28.6% at the end of the semester.

Second quartile

At the start of the semester only the Concentration model significantly predicted actual scores for second quartile students. As this model contained only students' predictions as a significant factor, income, ethnicity, generation status, and theory of intelligence were not significant factors for the second quartile at the start of the semester. At the end of the semester, however, theory of intelligence was a significant factor for the Motivation model (β = .244, p = .018). Predicted score remained a stronger predictor than theory of intelligence ($\beta = .455$; $p \leq .001$). Also at the end of the semester, generation status ($\beta = .243$; $p = .021$) joined prediction scores ($\beta = .311$; $p = .001$) as significant factors for the Study Aids model.

In this quartile, all Skill factors went from having non-significant models at the start of the semester to explaining a small amount of variance in actual scores at the end of the semester. In fact, three of the lowest four explanatory models for the second quartile fell within the Skill component. At the end of the semester, the Selecting Main Ideas model explained 8.0%, the Test Taking model explained 8.6%, and the Information Processing model explained 12.6%). Similarly, all Will factors moved from having non-significant models to explaining a moderate amount of variance. At the end of the semester, the Attitude model explained 12.7%, the Anxiety model explained 21.5%, and the Motivation model explained 29.1%).

Third quartile

Of all models, across all factors at both the start and the end of the semester, the third quartile model for Concentration captured the largest amount of variance in final actual score (31.8%). Significant factors in this model included predicted score (β = .477; $p \leq .001$) and income (β = -.239; p =.011). At the beginning of the semester, no significant model included income, ethnicity, generation status, or theory of intelligence as a significant predictor. At the end of the semester, however, theory of intelligence was a predictor in the Motivation (β = .233; p =.027) and the Study Aids (β = .221; p =.046) models for third quartile students. Student prediction scores remained strongly significant in the final Motivation and Study Aid models. In the end of semester Concentration model for the third quartile, income (β = -.239; p =.011) and student predictions were both significant factors (β = .477; $p \leq .001$).

The only factor not to have a significant model at the end of the semester was the third quartile model for Attitude; both the initial and final models for Attitude in the third quartile were not significant. Attitude was not significant or was low for both the third and fourth/top quartiles at the end of the semester and is the least predictive at the end of the semester across all Will components.

Top quartile

There were only two non-significant models at the start of the semester: Motivation (Will) and Self Testing (Self Regulation). At the beginning of the semester, theory of intelligence was a signification predictor in the Study Aids model (β = .221; p

$= .046$), but at the end it was no longer significant. Predicted score remained a stronger predictor than theory of intelligence in that initial model ($\beta = .403$; $p \leq .001$). Income, ethnicity, and generation status were not significant factors at any time point for any scale for the top quartile students.

At the end of the semester, the models explaining the most variance in actual scores for the top quartile students were for the three Skill factors: Information Processing (29.2%), Test Taking (30.9%), and Selecting Main Ideas (31.7%). In contrast, Test Taking and Information processing were two of the lowest three for the bottom quartile and Selecting Main Ideas and Test Taking were the lowest two for the second quartile.

Chapter Five: Discussion

The purpose for this study was to test hypotheses about the accuracy of students' strategic learning self-assessments using a sample of students enrolled in an undergraduate learning frameworks course at a highly competitive research institution. Previous studies demonstrated that learning frameworks courses significantly improve grade point averages, semester-to-semester retention rates, and graduation rates (Weinstein, 1994; Weinstein et al., 1997). Less is known, however, about changes that happen during the semester. Researchers have found that students tend to overestimate their academic abilities (Miller & Geraci, 2011), but that improving participant skill levels increases their ability to recognize the limitations of their abilities (Kruger & Dunning, 2009). This study builds on the existing learning frameworks and calibration literatures and addresses the following research questions: Does students' calibration accuracy improve from the beginning to the end of a semester-long strategic learning course? Does generation status influence calibration? What is the relationship between an individual's theory of intelligence and their strategic learning calibration? And, what is the relationship between accurate self-assessment and demographic factors such as family income and ethnicity?

Method and procedure of the study included self and objective assessments of strategic learning for ten learning factors known to impact student success. Measurements took place at two time points, beginning and end of the semester, for a sample of 507 university students in 22 sections of a lower division educational psychology course. Students may enroll in this course as a precautionary measure to prevent negative academic outcomes, or an academic advisor may suggest enrolling in this course after a student is already struggling to meet the academic requirements of the institution. Students assessed their level of strategic learning and then completed the corresponding

10-scale LASSI instrument, received feedback on their strategic learning level for each scale, and reflected on the discrepancies between self-assessed (predicted) score and actual score. I used mixed ANOVA and regression analyses to identify how accurate students were at the beginning of the semester, how accurate they were at the end of the semester, if this difference was significant, and if other factors – a student's theory of intelligence, parental education level, family income, and ethnicity – played roles in the accuracy of these self assessments. I was particularly interested in the extent to which the least strategic students became more accurate in their self-assessments. In this chapter I summarize the results of these analyses, discuss these findings in relation to the stated research questions, and then provide practical implications of this study and suggestions for future research on this topic.

Overall, three key findings emerged from the current study: 1) Students' initial self-assessments were inaccurate and, for the most part, students overestimated their actual strategic learning capabilities, 2) self-assessments are amenable to change and accuracy can improve within a learning frameworks course, especially among the least strategic learners in this sample, and 3) parental education level impacted actual level of strategic learning for some factors at the beginning of the semester, but by the end of the semester, it was no longer a significant predictor.

Actual strategic learning improvements

A nod to the positive impact this course had on strategic learning, students in all quartiles increased their self-reported levels of strategic learning on nearly all LASSI scales. Prior research using the LASSI instrument to determine the effectiveness of learning frameworks type courses also found statistically significant increases from pretest percentiles to posttest percentiles for every LASSI scale, with researchers indicating "that activities and content of the course were effective in improving the students' awareness about and use of study habits and learning strategies" (Dill, 2014, p. 32). Other researchers, conducting studies to assess the effectiveness of the learning frameworks course used in this study, have found the 10 learning factors (as measured by the LASSI) to contribute to academic achievement and persistence in college (Weinstein, 1987; Weinstein, 1994).

Hattie, Biggs, and Purdie (1996) have suggested that it is very difficult to change the study skills that students have acquired over many years of study, and they assert that for most study skill programs, changes in on study skills are minimal. Dembo and Seli (2004) suggest four reasons why individuals have difficulty changing their academic behaviors: (a) they believe they can't change, (b) they don't want to change, (c) they don't know what to change, or (d) they don't know how to change. This course addressed all four of these reasons. Most pertinent to the current study is that the calibration accuracy activity used at the beginning of the semester helps students identify what they need to change (c) and sets them up to help them try to change some of those behaviors (d). It is plausible that the self-assessment activity used in this study, and the other elements of the course, helped students alter their academic beliefs and behaviors.

As the end of the semester results demonstrated, there was a change in strategic learning in this course. Whether this change, as measured on the LASSI assessment, holds in minute-to-minute self-regulation activities was beyond the scope of this study, as was the long-term effectiveness of the course. These outcomes cannot be measured without gathering additional post-course data. However, the results of this study are consistent with previous studies that did measure these post course outcomes and that the content and delivery of the course materials enhanced students' strategic learning capabilities.

Even though students scoring in the lowest quartile on each learning factor showed remarkable improvement in their strategic learning, they still ended the semester with mean scores across all 10 learning factors under 55%. According to the guidance provided by LASSI authors, students how score below 75 till need assistance to improve (Weinstein & Palmer, 2002). Is this increase truly enough to influence students' academic behaviors going forward? How much improvement is reasonable in a learning frameworks course, and how might the changes in thinking and behavior initiated in a learning frameworks course need to be reinforced in other campus interventions? The lowest performing students may benefit from additional time and effort toward acquiring these learning strategies and skills. Therefore, it is important to consider this course as part of a broader system of supports.

Self-assessment accuracy

As hypothesized, at the start of the semester, students were not accurate predictors of their strategic learning abilities on any of the 10 LASSI strategic learning factors. This is consistent with the robust findings from calibration research on everything from reading comprehension, to reasoning abilities, and general mathematics skills that generally suggest that individuals overestimate their capabilities and that self-assessments tend to be inaccurate. Over the course of the semester all quartiles saw improvements in calibration accuracy and most quartiles saw reductions in bias.

The lowest performing students were the most functionally overconfident; their strategic learning self-assessments were less accurate and more overconfident than their highly strategic peers. However, the least strategic students did demonstrate greater improvement in calibration accuracy than the highly strategic students. The bottom quartile continued to earn the lowest actual scores and the maximum mean score for the bottom quartile was 54.0 (Selecting Main Ideas). The lowest mean accuracy score in the bottom quartile improved from 57.7 (Attitude) to 24.8 (also Attitude). In comparison, the lowest mean accuracy score for the top quartile improved from 18.4 (Information Processing) to 9.0 (Test Taking). The bottom quartile saw the largest improvement in percentage of actual score explained by self-assessment across all learning factors as 9 factors improved explanation by at least 11% from the beginning to the end of the semester. The bottom quartile was the only group to have at least 6 factors improve by over 16%.

Given that the least strategic students were those with the greatest room to make drastic assessment improvements, these findings are not surprising. Highly strategic students started off the semester with more accurate self-assessments, therefore their improvement from the beginning to the end of the semester could not be as large as the accuracy changes for the least strategic students in the course. Similar to the Miller and Geraci (2011) findings that low performing students continued to show more functional overconfidence than high performing students did after engaging in monitoring and reflecting exercises for a whole semester, the results of this study suggest that low and high performing students differ in accuracy at both the beginning and the end of the semester. This held not only for students in the bottom quartile, but also for the second quartile, indicating that the bottom half of the sample differed from the top quartile.

Domain familiarity

Lin and Zabrucky (1998) stressed the importance of domain knowledge, suggesting that, "the discrepancy between perceived and actual performance found in previous studies may be the result of readers' lack of expertise knowledge" (p. 342). Their focus was on metacomprehension, but the same idea applies to metacognition. Domain familiarity could have had two separate influences on this study. Initial domain knowledge could be responsible for the magnitude of overestimation of initial levels of strategic learning whereas increased domain familiarity acquired from engaging in the course content during the semester could have led to improvements in self-assessment accuracy at the end of the semester.

One might expect individuals to have a better sense of their competence within a domain in which they are highly familiar. This initial level of domain knowledge might explain the better accuracy for "popular" study skill strategies – coping with anxiety, time management, and concentration – found for the bottom quartile students in this study. One explanation for this precision is that students entered the class more familiar with what time management encompasses as compared to having a concrete understanding of what other learning factors, such as self-testing and motivation, entail. Previous research investigating the connection between domain knowledge and calibration found that calibration accuracy is positively related to prior knowledge (Tobias & Everson, 2009), that experts display better accuracy than novices (Griffin et al., 2009), and that this domain knowledge usually improves performance on domain-related text comprehension and problem solving (Chi, Glaser & Farr, 1988; Ericsson & Kintsch, 1995). These studies are consistent with the Kruger-Dunning "unskilled and unaware effect" that posits that low performers overestimate performance because they lack domain knowledge and metacognitive insight.

If this effect held in the current study, that is, if students were most accurate for the learning factors with which they had the most domain knowledge, we would expect to see, for example, that actual Time Management LASSI scores would be among the highest actual scores across all of the scales. This was not the case. Mean initial actual Time Management scores for the bottom quartile (4.7), 2nd quartile (19.9), and 3rd quartile (43.4) were among the lowest actual scores. We would also expect Time Management accuracy to be best for the 2nd, 3rd, and top quartiles also. This did not hold for all quartiles: each quartile had a different 'most accurate' factor (Information Processing (2^{nd}), Study Aids (3^{rd}), and Concentration (top quartile)) at the beginning of the semester. Instead of supporting the unskilled and unaware effect, these findings are more consistent with research findings that although students may be overconfident in their abilities, this overconfidence is higher for better-known topics than for lesser-known topics and there is an awareness of this discrepancy (Miller and Geraci, 2011; Shanks and Serra, 2014).

Domain knowledge may have also influenced end of semester self-assessment accuracy as the topics studied in the course are the same strategic learning topics assessed on the LASSI instrument used in this study. Engaging in the course content could have led to improvements in actual level of strategic learning (measured by the self-report responses on the LASSI scales) and it could have influenced self-assessment accuracy. In previous calibration studies, as content knowledge increased, so did the accuracy of judgments about content mastery (Maki & Serra, 1992), leading researchers to conclude that improving content mastery can improve judgments. Additionally, students completed the same LASSI assessment, answering the same questions at the end of the semester. In previous research using identical items on pre- and post-tests, researchers have found high (accurate) calibration (Glenberg et al. 1987).

Feedback and strategy instruction

Accuracy has been shown to increase when participants receive feedback and have an opportunity to practice self-assessing (Glenberg & Epstein, 1985; Bol, 2005; Huff & Nietfeld, 2009; Thiede, Redford, Wiley, & Griffin, 2012). The majority of these studies focused on strategy training within one domain, training students to use "reading comprehension" strategies in a literacy course or "statistics" strategies within a statistics setting (Nietfeld, 2002). The course used in this study addressed learning strategies more generally in an effort to enhance students' adoption of effective strategies across domains. Gutierrez and Schraw (2015) took a similar approach in their investigation of a strategy intervention designed to introduce students to different learning strategies and improve monitoring and control processes. In their study, Gutierrez and Schraw introduced strategies, explained them in detail, demonstrated them, and then had students practice using the strategies during a 1-hour session. To test the effectiveness of the intervention, researchers had students engage with a stimulus text and provided performance assessments at two time points, before and after the 1-hour strategy session. They found that students who participated in the strategy instruction treatment had improved performance and calibration when compared to students in the control group who did not participate in the strategy instruction. Gutierrez and Schraw only used one stimulus text to measure the effectiveness of this strategy instruction, leaving open the question of whether the effect of the intervention persists across different domains. The current study does not resolve that issue, but does demonstrate that strategy instruction can be "general" and can result in better self-assessments.

What is clear from the general knowledge and skill specific calibration strategy training is that information that is precise and meaningful can have the greatest impact on reducing over and underestimation. And the feedback students in this course received was personalized and precise. Receiving feedback on 10 separate learning factors provided students with a baseline representation of their strategic learning abilities and offered an idea for where students should focus efforts in addressing patterns of thinking or behavior that may not be serving their academic pursuits well. An additional benefit of having students assess themselves on all 10 strategic learning factors is that it helps prevent against self-serving bias. According to theories of self-serving bias, individuals interpret skills, talents, and abilities as reflective of broad traits while dismissing their weaknesses as reflective of nothing. Thus, when given feedback on one weakness, they do not often question their overall ability but rather compartmentalize that weakness and ignore how it might be related to overall ability. In this study, students were given feedback about 10 facets of strategic learning, and, in the course of the semester, self-assessments for each factor improved. By not making a global evaluation of strategic learning, the process used in this study may have helped minimize the effect of this self-serving bias.

Social desirability and peer learning

Some of the improvement in calibration accuracy could be attributed to changes in students' social desirability bias. Social desirability bias captures participants' tendency to respond to questions in a way that will help them adhere to social norms or to behave in a way they think someone else wants them to behave instead of responding truthfully without regard to how they are viewed by others. This can include overestimating "good behavior" or underestimating "bad," or undesirable behavior. Social desirability was not measured in the current study, but it could have contributed to the magnitude of overestimation of strategic learning capabilities at the beginning of the semester.

At the start of the semester, instructors and students are still building a trusting relationship. Despite assurances that the LASSI self-assessments and responses were to be used only by the student, it is possible that students' did not trust that the assessment was for their own personal use and that instructors would not use their performance on the LASSI to judge them. Students' desire to make a good impression could have played a role in their actual LASSI assessment scores and in their self-assessments. End of semester accuracy scores could have improved because students were being more honest about their own capabilities and had less of a desire to show favorable results to external parties.

Another explanation for improved end-of-semester accuracy is that during the course students develop an awareness of “normal” and/or positive collegiate learning behaviors. Dunning and Kruger (2009) theorized that the negative bias indicative of the highest performing students is the result of these students not having an accurate understanding of how well their peers do. In the class used in this study, discussions focused on ”typical” or “common” learning thoughts and behaviors, and students worked collaboratively on in-class activities. These activities provided numerous opportunities for all students to obtain useful information about the strategies their peers are using and how they compare to their peers. At the end of the semester, students in this study may have had more accurate self-assessments because they had better knowledge of their peers, and this may have been especially important for the students in the highest quartile.

Accuracy on the Skill factors

According to regression models for the study sample as a whole, student self-assessments for the Skill factors, Information Processing (18.1%), Selecting Main Ideas (20.9%), and Test Taking (21.1%), ranked among the lowest in explaining the amount of variance in initial actual scores. Test Taking (24.0%) and Information Processing (27.4%) remained among the lowest predictive models at the end of the semester as well. Interestingly, the end of semester regression model predicting actual score from self-assessed prediction for the three Skill factors explained the most amount of actual score variance for the top quartile. These results indicate that, although there may have been significant improvement in accuracy overall, the mechanisms driving improved self-assessment with respect to the Skill factors need to be investigated further. One possible explanation is that students tend to be much more accurate when they are asked concrete questions about precisely defined behavior rather than asked more global and abstract questions less specifically tailored to the particular task at hand (Bandura, 1986). Another possible explanation is that students in this course showed greater increases actual strategic learning (as measured by self-reports on the LASSI instrument) on the Skill factors and the increase in self-assessment accuracy is due to higher Skill scores.

Generation status and Will factors

According to the repeated measure ANOVAS that included generation status as a between subjects factor, there was no main effect of generation status for any of the scales, but there were significant main effects of time and quartile and significant time x quartile interactions. There were significant time x quartile x generation status interaction for Anxiety, Motivation, and Selecting Main Ideas at the $p < .05$ level, as well. This same interaction became significant for the Attitude factor at a $p < .10$ level. Follow up tests for Anxiety, Motivation, and Selecting Main Ideas revealed an inconsistent pattern of significant accuracy differences between continuing and G_1 students. These results are somewhat consistent with the regression analyses results. At the start of the semester, generation status was a significant predictor in the most explanatory regression models for factors across all three MSL components: Information Processing, Anxiety, Motivation, Study Aids, and Time Management. For these scales, the models associate higher parental education with higher actual scores on these four factors. At the end of the semester, however, generation status was not a significant predictor in any of the overall models.

From the above results, it appears that most of the generation differences occur for Will factors – Anxiety, Attitude, and Motivation. For Anxiety, the ANOVA results indicated that continuing generation students made more accurate self-assessments than G_1 students at the beginning of the semester and that G_1 students were more positively biased than their continuing generation peers. However, by the end of the semester, both groups became more accurate and differences in accuracy no longer existed, and G_1

students were no longer more positively biased than their continuing generation peers. All students in the lowest quartile improved their Anxiety accuracy, but continuing students showed greater accuracy improvement than their G_1 peers. On the Motivation factor, t-tests for the bottom quartile indicated that at the start of the semester, G_1 students differed from continuing generation students. At the end of the semester, however, there was no significant difference between G_1 students and continuing generation students in the bottom quartile.

Interestingly, the distribution of G_1 students across quartiles was not consistent for all scales. A higher proportion of continuing generation students placed into the top two quartiles for every scale; Anxiety and Motivation, in particular, had significantly larger proportions of G_1 students in the lower quartiles. For Anxiety, this result is not surprising. This factor measures a student's ability to cope with anxiety; sample items include *I worry that I will flunk out of school* and *I get so nervous and confused when taking an examination that I fail to answer the questions to the best of my ability*. Finding more G_1 students in these lower quartiles indicates that G_1 students in this sample were less able to cope with anxiety than their continuing generation peers, affirming previous research that G_1 students are more likely to fear failing out of college than their continuing generation peers.

The G_1/continuing generation differences for Motivation are more surprising. The Motivation scale measures the extent to which students accept responsibility for performing the specific tasks related to school success. Sample items from Motivation scale include: *I set high standards for myself in school* and *Even if I do not like an assignment, I am able to get myself to work on it*. Having more G_1 students in the lowest quartiles seems contrary to the idea that these students are highly motivated to be successful in college, especially for the population in this study. Closer examination of the Motivation items finds that they generally focus internally, on the doing of academic work. This may be different from other studies investigating G_1 student motivation that look at more broad conceptions of Motivation (e.g., external or introjected motivational factors). Another possibility for differences is that G_1 students and continuing generation students differ on their interpretations of some of these items, for example, their representation of "high standards." The instrument used in this study also might not capture behaviors they rely on to build academic capital. It could be that the G_1 students in this study have developed academic capital that is not measured by the current instrument. Further research in this area is needed to better understand these findings.

Self assessment accuracy and growth mindset

Theory of intelligence was a significant predictor in initial models for Test Taking, Attitude, Motivation, and Study Aids. At the end of the semester, a more malleable mindset continued to be associated with higher actual scores for Test Taking, Attitude, and Motivation. It is not surprising that beliefs about the malleability of intelligence impact accuracy for Will elements. It is interesting that theory of intelligence was not a factor in any of the quartile level regression analyses, nor does it appear that theory of intelligence was a significant contributor for those factors on which students showed the most improvement. Though unanticipated, seeing improvements in strategic learning capabilities regardless of a student's theory of intelligence could be good news for learning frameworks instructors as accuracy improved on most scales without theory of intelligence playing a significant role. Adopting a growth mindset is not a prerequisite to effective metacognition and to improving metacognitive monitoring.

This connection with growth mindset should be interpreted with caution, however. Students in this sample tended to endorse a growth theory of intelligence. For the overall sample, mean TOI was 2.8 (*SD* = 1.1), on a maximum scale of 4, indicating stronger beliefs that intelligence is malleable. The lowest TOI mean for a quartile was for a bottom quartile (M = 2.5; SD = 1.1). This could be an artifact of the population from which this sample was drawn. It could also be representative of the trend in education to discuss more explicitly fixed and growth mindsets. Additionally, the theory of intelligence measure used in this study consisted of three items. Despite its extensive use in other mindset literature, other instruments containing more items that tap into different dimensions of fixed and growth mindsets are also available. It is possible that a different instrument could impact the study results.

Income and ethnicity

Income did not appear as a significant predictor in many overall models, and I could discern no pattern to the models in which it was significant. At the beginning of the semester, income was a significant predictor for two Skill factors – Test Taking and Information Processing. At the end, it no longer significantly contributed to the Test Taking and Information Processing models, but did now contribute to the most explanatory Time Management model.

Based on the regression models for the overall sample, it appears that *ethnicity* was a significant predictor for six scales: Anxiety, Attitude, Information Processing, Motivation, Self-Testing, and Test Taking. This means that ethnicity was a significant predictor for the beginning of semester models for all three Will factors. However, ethnicity was not a significant predictor for any of the Will factors when the analyses were conducted on a quartile-by-quartile basis. Ethnicity was only a significant predictor in two quartile models – Test Taking and Study Aids at the beginning of the semester for the bottom quartile. At the end of the semester, ethnicity was not a significant predictor in *any* of the overall regression models.

Taken together, the findings for income and ethnicity indicate that these factors may have strong influences on academic achievement and students' motivation, attitude and interest in learning and achieving college success. They may also affect their ability to cope with worry about school and academic performance, and their self-discipline, commitment, and willingness to do what needs to be done to achieve the outcomes they desire. However, they are not consistently predictive of strategic learning capabilities in the Skill or Self-Regulation components, and their effect is mitigated after participating in the activities of the course used in this study.

Importance of the study in the field

To my knowledge, no other study has investigated the accuracy of students' perceptions about their strategic learning when measured in n actual course context. The preponderance of calibration literature focuses on the accuracy of perceptions on tests that focus on declarative facts: general knowledge items with which the participants had no extensive professional experience, recall of paired items (Dunlowsky and Hertzog, 2000), grades on an exam (Hacker, Bol, Horgan, and Rakow, 2000), whether one has answered a specific verbal or mathematical content question correctly, etc. The current study built upon Hacker et al.'s (2000) work investigating calibration for a criterion outcome that was meaningful to the student, upon social psychology literature on unrealistic optimism, and upon Gutierrez and Schraw's (2015) work to create a general metacognitive strategy intervention to help students be successful across domains. This study also extends calibration theory to perceptions of capabilities in a more general sense and adds similar trends in accuracy and bias to the calibration literature. Overall, these findings add support to theory and research suggesting that students across all levels of actual ability hold inaccurate perceptions of themselves (Dunning, 2005), and I have offered a variety of explanations for how participating in a learning frameworks course helped students become more accurate in their self perceptions.

By using regression analyses in addition to the mixed ANOVAs, this study added evidence to the calibration literature about the strength of self-assessments in predicting actual LASSI scores. Within research on teaching and learning, the effect size for self-assessment predictions for all of the regression analyses in this study were large (Keith, 2006). It was useful to see that strong predictors (e.g., G_1 status, ethnicity, and family income) in beginning-of-semester models no longer held at the end of the semester. This method of analysis also illuminated the extent to which other factors might help explain actual LASSI scores.

This study also contributes a new understanding of learning frameworks courses. Previous research in this field has focused on what happens to students after they take a learning frameworks course (e.g., their grade point average and their subsequent enrollment and graduation rates) or on whether or not the course led to changes in their strategic learning thinking and behaviors. This study targeted students' metacognition – how they were thinking about their own thinking and behaviors. Consistent with previous research, I found that metacognitive abilities are malleable (Pressley & Ghatala, 1990) and that self-assessments can become more accurate if students participate in structured exercises that incorporate the use of external assessments combined with self-reflection. The findings of the current study support previous research that shows that strategy training improves accuracy of predictions (Nietfeld and Schraw, 2002) while moving from a lab-based experiment to classroom-based research, and underscores the value of using an assessment like the LASSI as a mirror for students to view themselves through. The goal of a learning frameworks course is to help students use self-regulation strategies and the calibration exercise used in this study can serve as a model activity that faculty members can use to help students recognize that they may be relying on faulty information (self-assessments about their skills as learners) during the monitoring and evaluating stages of the self-regulation cycle. As the course also included other opportunities for students to reflect on their own strategic learning thoughts and behaviors (e.g., in writing assignments, on exams, and in group discussions), the specific contribution of the LASSI self-assessment and reflection exercise cannot be isolated from the effects of the overall course in this study.

Although there was a slight impact of generation status on self-assessment accuracy at the beginning of the semester, at the end of the semester no differences in accuracy existed for first and continuing generation students. Because both groups became more accurate in their self-assessments from the beginning of the semester to the end, one interpretation is to say that the learning frameworks course intervention served both of these populations well. However, we cannot rule out the possibility that this finding is the result of the study population being a restricted sample of G_1 students. Future research in this area, especially research that delves into the social and cultural capital of G_1 students who have matriculated at a highly competitive Tier 1 research institution, would deepen our understanding of this finding.

Limitations

As with any study there are limitations to the generalizability of the results and the conclusions that can be drawn from the analyses conducted. As discussed above, students in this study applied to, were accepted, and chose to attend a highly competitive research-intensive institution. The characteristics that drew these students to this particular academic environment and the characteristics that enabled them to earn high grades in high school may be different from characteristics of students attending other 4-year and 2-year institutions. This may be especially salient for the analyses comparing first-generation and continuing generation students. The sample of first generation students in this study does not have common G_1 characteristics (non English speakers, nontraditional students, low income). Additionally, this is an elective course that does not count toward a specific major and students enrolled in this course may not be representative of the overall University. Student motivations for enrolling in the course should be included in future studies, to determine whether these findings hold for students who enroll in the course in order to get off academic probation as well as students who proactively enroll to prevent poor academic outcomes. Replicating this study and drawing a sample from other 4-year and 2-year institutions, especially across different learning frameworks course delivery methods (e.g., face-to-face, online, hybrid), would better capture the courses that serve the wider G_1 population. Additionally, due to sample size limitations for the quartile comparisons, the current study dichotomized generation status. Regression analyses using a wider range of parental education levels would provide useful information about the impact of incrementally increasing parental educational level. Given this, the current results should be generalized with caution and highlight their applicability to students who are accepted into and enroll in a competitive post-secondary institution.

Another limitation of this study is that gender was not included in the analyses as that was not a demographic factor students were asked to share on the student information form. This could impact both actual strategic learning level and self-assessments. Few studies have attempted to identify potential gender differences in strategic learning capabilities and the results of those studies are somewhat mixed. Using the metacognitive awareness inventory, Cooper (2004) found no significant differences in metacognition between male and female participants. Using the LASSI instrument, Yip (2007) and Felder et al. (1995) found that women had higher strategic learning mean scores than men, whereas Prus, et al. (1995) found only slight differences between men and women. Other researchers have found differences by Model of Strategic Learning components, with female students scoring significantly higher for the self-regulation and will components and male students scoring significantly higher for the skill component (Downing, Chan, Downing, Kwong, & Lam, 2008). In the current study, assignment to quartiles was based on actual scale scores at the start of the semester; therefore, a latent effect of gender could have been missed using this methodology and sample.

Self-assessments may also vary by gender, and this effect may be especially salient for subpopulations of students. For example, Woodcock and Bairaktarova (2015) found that male engineering students made more accurate assessments of their performance than their female peers, and that female engineering students underestimated their performance compared to their male counterparts. These effects held even after controlling for actual performance differences, familiarity with the task, and task difficulty. The current study did not include many engineering students and gender differences in non-STEM fields may not be as stark. Nevertheless, the possibility exists and should be studied further.

Finally, at the beginning of the semester in the current study, instructors gave a brief overview of the LASSI scales before students completed the self-assessment predictions and then completed the LASSI instrument. However, simply taking the LASSI raises students' awareness and improves knowledge of the specific strategic learning thoughts and behaviors. Experiencing the 80 items makes strategic learning more concrete for students and moves them away from abstract ideas of being a "good" or "bad" student or having "good" or "bad" Time Management skills for example. The LASSI scale items are specific in that they refer to thoughts and behaviors within a learning factor but they are general in that they prompt students to consider their thinking and academic behaviors usually, not in reference to a specific course. Thus, none of the scales captures a general picture of how metacognitively aware students are when they start the semester. This study could be repeated using a control group that does not do the prediction exercise to help isolate the effect of the prediction from the effect of increasing knowledge and include a general measure of metacognitive awareness to assess whether or not general metacognitive awareness influenced study results.

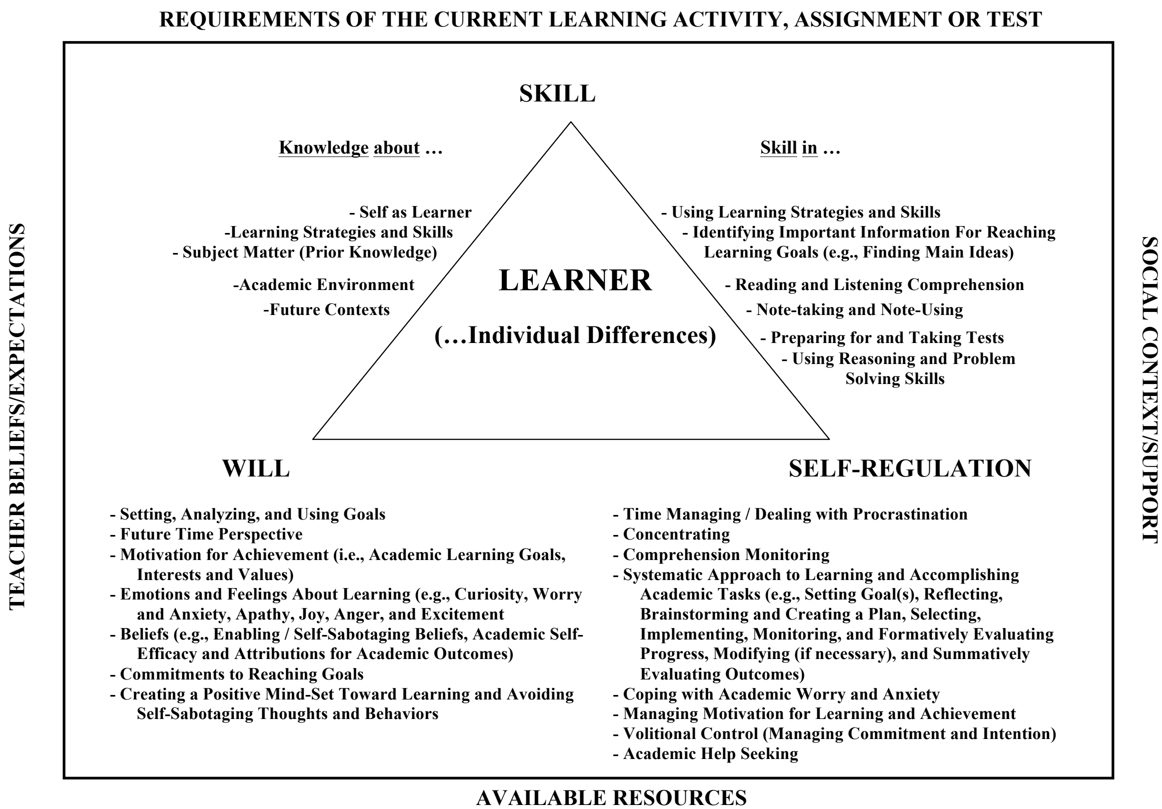
Additional ideas for future studies

In the current study, students were placed into quartiles on a scale-by-scale basis; if their actual Anxiety score was in the bottom 25% of students in this sample, they placed into the bottom quartile for the Anxiety scale. That same student may have placed into the second, third, or top quartile on any of the other nine scales. Thus, this study did not look at students holistically. Still unknown is how accuracy improves for students who begin the semester scoring low in more than one of these strategic learning areas. As a first step in addressing these questions, researchers could identify the number of factors on which a student is low (2, 3, 4, etc.), cluster students based on this number, and rerun the regression analyses for these clusters. Follow up testing could parse out specific learning factors that drive the clusters and answer the question, 'how does accuracy improve for students who begin the semester low in one or more areas.

As was mentioned above, additional work could be done to disambiguate the influence of understanding the items on the assessment from the impact of the course. Another suggestion to help parse out the understanding of each topic from a student's ability to self-assess performance on that learning factor is to add a post-diction assessment to the methodology. As was the methodology in this current study, the instructor would provide an overview of the Model of Strategic learning and the 10 scales and then have the students record their self-assessments. Then, the students would complete the assessment. Instead of immediately comparing their self-assessment to their actual performance, students would be asked to do a post-diction assessment in which they would self-assess again, this time having more information about each of the scales by having engaged with all of the items. Maki and Sera (1992) found improvement in accuracy from prediction to post diction when students followed a similar procedure in their study of reading calibration, and they attributed the accuracy improvement to students using newly acquired knowledge that came from taking the assessment. Measuring change magnitude and direction between prediction and post diction on the pre-assessment could help isolate the effects of self-assessment/reflection from that of domain knowledge, and further our understanding of students' initial strategic learning self-knowledge.

Future research is also needed to understand more about students who make the largest adjustments in self-assessments during the course. More closely examining the characteristics of those students who make the largest adjustments in self-perception can help institutions match support services (such as this class) to student support needs (e.g., if this class is the right intervention for a particular student). Qualitative measures, such as student learning autobiographies completed at the start of the semester or focus groups at the end of the semester can be used to identify themes for those who made the most (or least) improvement in accuracy. Such an expansion would also allow researchers to measure or incorporate social and cultural capital variables to measure their mediating effect on self-assessment accuracy for G_1 and continuing generation students. Additionally, following these students after they complete this course to assess their persistence and completion in comparison with students who do not take a learning frameworks course or who do not make large adjustments in self-perceptions of learning strategies could also provide valuable information used to match student supports with student needs.

Appendix A:
Model of Strategic Learning



Appendix B:
Institutional Review Board approval

OFFICE OF RESEARCH SUPPORT

THE UNIVERSITY OF TEXAS AT AUSTIN

P.O. Box 7426, Austin, Texas 78713 · Mail Code A3200
(512) 471-8871 · FAX (512) 471-8873

FWA # 00002030

Date: 04/13/16

PI: Nancy K Stano

Dept: Educational Psychology

Title: Improving College Student's Self-Knowledge Through Engagement in a Learning Framework Course

RE: Non-Human Subjects Research Determination

Dear Nancy K Stano:

The Office of Research Support (ORS) reviewed the above protocol submission request and determined it did not meet the criteria for human subjects research as defined in the Common Rule (45 CFR 46) or FDA Regulations (21 CFR 56). IRB review and oversight is not required because the activities involve:

☐ No human interactions
☐ Classroom activities used to teach methodology and technique
☐ Program evaluation where results are not generalized to other services or programs
☒ Secondary use of de-identified data set (no direct or links to identifiers)
☐ Obtaining information that is not about living individuals
☐ Obtaining information from publicly available sets
☐ Biographical research that is not generalizable beyond the individual
☐ Archival research using existing literature
☐ Other (Explain):

At this time you are free to begin your research as IRB approval is not necessary. You should retain this letter with the respective research documents as evidence that IRB review and oversight is not required.

If you have any questions contact the ORS by phone at (512) 471-8871 or via e-mail at orsc@uts.cc.utexas.edu.

Sincerely,

James Wilson, Ph.D.
Institutional Review Board Chair

Appendix C:
Prediction and actual means and standard deviations by scale

Anxiety

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	142	39.2	23.8	3.9	3.4	42.9	25.3	42.7	26.8
2nd Quartile	117	48.4	23.2	23.5	7.5	49.3	20.1	42.7	26.8
3rd Quartile	134	59.5	19.4	54.8	10.5	63.9	16.2	67.5	22.5
Top Quartile	114	73.7	24.9	86.4	7.0	84.2	17.0	84.6	17.8

Attitude

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	180	63.7	21.6	6.0	3.8	45.9	24.9	30.7	26.8
2nd Quartile	110	76.5	18.7	22.6	6.5	56.5	22.5	43.6	27.3
3rd Quartile	94	76.9	17.9	45.0	5.0	67.9	16.1	55.3	25.2
Top Quartile	123	83.5	13.5	73.9	11.8	79.2	12.9	70.56	21.8

Concentration

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	145	41.6	20.7	5.7	3.9	43.8	23.2	41.3	26.9
2nd Quartile	125	53.1	19.8	23.4	5.7	53.2	20.5	51.6	22.4
3rd Quartile	139	62.4	16.9	45.6	9.0	61.5	15.4	63.1	21.8
Top Quartile	98	75.2	16.5	78.6	10.3	79.1	14.3	77.7	19.4

Information Processing

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	126	51.2	19.4	6.6	5.2	50.4	25.2	50.2	29.2
2nd Quartile	163	58.5	18.4	35.6	10.1	62.4	17.2	68.1	21.8
3rd Quartile	129	62.9	19.0	65.9	8.4	72.0	14.9	77.4	16.2
Top Quartile	89	71.8	19.9	88.4	5.4	84.0	12.8	87.2	15.8

Motivation

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	136	52.4	21.2	10.4	6.5	49.0	26.3	42.9	27.1
2nd Quartile	117	62.5	18.6	32.3	7.0	60.0	18.5	58.4	26.3
3rd Quartile	126	68.7	19.6	60.8	7.2	71.3	14.7	69.9	22.3
Top Quartile	128	80.7	16.4	88.3	6.7	86.8	12.9	84.8	18.8

Self Testing

	Initial					Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	169	47.2	21.3	5.7	3.8	43.0	24.7	44.5	29.5
2nd Quartile	100	49.8	19.1	19.7	4.1	53.8	23.2	58.2	27.4
3rd Quartile	114	59.3	19.7	44.1	7.0	62.8	18.0	69.1	22.6
Top Quartile	124	66.1	20.0	74.6	11.5	77.4	16.6	79.5	18.8

Selecting Main Ideas

		Initial				Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	143	50.5	22.0	6.6	5.1	49.5	25.9	54.0	25.3
2nd Quartile	113	56.3	21.0	27.9	5.6	58.0	19.0	64.8	22.8
3rd Quartile	142	67.5	15.2	53.0	9.8	66.3	17.1	74.0	16.9
Top Quartile	109	70.9	18.3	81.1	9.3	82.8	12.4	84.2	13.9

Study Aids

		Initial				Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	132	47.3	21.0	6.8	5.2	44.4	24.5	44.6	27.6
2nd Quartile	154	55.7	22.9	33.0	8.9	58.8	18.6	62.7	24.6
3rd Quartile	105	64.3	18.6	62.3	6.2	70.7	16.3	75.4	18.9
Top Quartile	116	70.6	17.0	86.6	6.7	85.0	11.2	86.1	14.7

Test Taking

		Initial				Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	149	49.2	21.5	7.4	5.2	50.9	24.5	53.7	26.0
2nd Quartile	124	55.8	18.6	29.0	7.3	57.9	19.8	64.7	22.7
3rd Quartile	125	62.5	17.3	56.8	8.5	69.1	15.3	70.5	21.8
Top Quartile	109	68.5	19.8	83.5	7.0	83.5	11.5	84.9	12.9

Time Management

		Initial				Final			
		Prediction		Actual		Prediction		Actual	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	173	37.6	20.2	4.7	3.9	44.2	24.7	38.9	26.9
2nd Quartile	87	53.9	19.8	19.9	4.2	52.2	19.8	52.7	23.8
3rd Quartile	140	59.3	17.1	43.4	10.7	61.7	18.2	62.0	25.9
Top Quartile	107	69.8	19.3	80.1	10.1	80.7	15.8	81.3	15.0

Appendix D:
Zero-order correlations for study variables

*Zero-order Correlations for Study Variables – **Initial Predictions***

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. FG Status	–														
2. Age	.067	–													
3. GPA	-.213**	.026	–												
4. Fam. Inc.	-.450**	-.044	.276**	–											
5. TOI initial	.021	-.016	.013	-.093	–										
6. ANX	-.002	.004	.148**	.090	.045	–									
7. ATT	.111*	.042	.217**	-.009	.162**	.154**	–								
8. CON	.023	.048	.162**	.033	.085	.215**	.482**	–							
9. INP	.022	.112*	.115*	.115*	.097	.221**	.408**	.576**	–						
10. MOT	.055	.017	.279**	.011	.136**	.106*	.613**	.574**	.433	–					
11. SFT	-.045	.141**	.206**	.130**	.080	.192**	.349**	.469**	.536**	.472**	–				
12. SMI	-.085	.144**	.120*	.214**	.087	.285**	.353**	.455**	.533**	.374**	.572**	–			
13. STA	-.025	.076	.142**	.046	.163**	.152**	.382**	.389**	.523**	.468**	.512**	.553**	–		
14. TMT	.012	.021	.249**	.057	.192**	.164**	.428**	.570**	.387**	.608**	.436**	.350**	.497**	–	
15. TST	-.038	.089	.281**	.126**	.058	.270**	.446**	.545**	.552**	.483**	.592**	.598**	.541**	.561**	–

Note. FG Status = First generation status; Fam. Inc.=Family income; TOI initial = Theory of Intelligence; ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self Testing; SMI = Selecting Main Ideas; STA = Study Aids; TMT = Time Management; TST = Test Taking

*Zero-order Correlations for Study Variables – **Initial Actual Performance***

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1. FG Status	–														
2. Age	.067	–													
3. GPA	-.213**	.026	–												
4. Fam. Inc.	-.450**	-.044	.276**	–											
5. TOI initial	.021	-.016	.013	-.093	–										
6. ANX	-.110*	-.004	.230**	.174**	-.002	–									
7. ATT	.003	-.008	.187**	-.043	.249**	.238**	–								
8. CON	-.033	.050	.209**	.048	.122*	.388**	.516**	–							
9. INP	-.079	.200**	.157**	-.009	.065	.129**	.278**	.340**	–						
10. MOT	-.123**	.016	.437**	.056	.177**	.238**	.566**	.578**	.408**	–					
11. SFT	-.067	.058	.175**	.032	.073	.091*	.385**	.420**	.565**	.510**	–				
12. SMI	-.082	.056	.129*	.184**	.067	.532**	.347**	.572**	.356**	.378**	.336**	–			
13. STA	-.100*	-.033	.249**	.026	.167**	-.021	.414**	.361**	.418**	.545**	.574**	.168**	–		
14. TMT	-.062	.020	.300**	.039	.161**	.172**	.451**	.649**	.312**	.667**	.522**	.325**	.537**	–	
15. TST	-.158**	.080	.328**	.237**	.080	.563**	.424**	.564**	.326**	.523**	.364**	.753**	.235**	.422**	–

Note. FG Status = First generation status; Fam. Inc.=Family income; TOI initial = Theory of Intelligence; ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self Testing; SMI = Selecting Main Ideas; STA = Study Aids; TMT = Time Management; TST = Test Taking

*Zero-order Correlations for Study Variables – **Final Predictions***

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. FG Status	–														
2. Age	.067	–													
3. GPA	-.213**	.026	–												
4. Fam. Inc.	-.450**	-.044	.276**	–											
5. TOI initial	.021	-.016	.013	-.093	–										
6. ANX	-.004	.030	.117*	.089	.041	–									
7. ATT	.083	-.001	.079	-.058	.165**	.404**	–								
8. CON	.002	.037	.092	.005	.114*	.461**	.578**	–							
9. INP	.014	.135**	.070	.032	.110*	.295**	.480**	.517**	–						
10. MOT	-.029	-.016	.235**	.027	.188**	.274**	.662**	.585**	.529**	–					
11. SFT	.010	.034	.101	.027	.083	.292**	.521**	.559**	.622**	.567**	–				
12. SMI	-.025	.094**	.022	.123**	.070	.478**	.443**	.540**	.629**	.423**	.569**	–			
13. STA	-.041	.000	.118*	.014	.154**	.157**	.507**	.484**	.509**	.577**	.649**	.407**	–		
14. TMT	.058	.011	.116*	-.021	.173**	.314**	.560**	.655**	.453**	.668**	.575**	.413**	.605**	–	
15. TST	-.082	.050	.184**	.153**	.097	.459**	.532**	.534**	.560**	.536**	.584**	.674**	.475**	.522**	–

Note. FG Status = First generation status; Fam. Inc.=Family income; TOI initial = Theory of Intelligence; ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self Testing; SMI = Selecting Main Ideas; STA = Study Aids; TMT = Time Management; TST = Test Taking

*Zero-order Correlations for Study Variables – **Final Actual Performance***

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. FG Status	–														
2. Age	.067	–													
3. GPA	-.213**	.026	–												
4. Fam. Inc.	-.450**	-.044	.276**	–											
5. TOI initial	.021	-.016	.013	-.093	–										
6. ANX	-.019	.032	.077	.037	.042	–									
7. ATT	.038	.025	.128*	-.048	.216**	.353**	–								
8. CON	.101*	-.001	.040	-.094*	.114*	.494**	.558**	–							
9. INP	-.043	.055	.067	.006	.089	.275**	.494**	.526**	–						
10. MOT	-.016	-.058	.288**	.032	.266**	.328**	.640**	.560**	.514**	–					
11. SFT	.014	-.021	.035	-.017	.067	.281**	.487**	.548**	.673**	.524**	–				
12. SMI	.011	.074	-.043	.020	.069	.353**	.432**	.568**	.475**	.450**	.438**	–			
13. STA	-.105*	-.042	.102*	.022	.155**	.214**	.516**	.458**	.544**	.572**	.578**	.332**	–		
14. TMT	.069	-.023	.085	-.081	.149**	.295**	.541**	.663**	.471**	.629**	.558**	.355**	.598**	–	
15. TST	-.032	.012	.115*	.026	.134**	.577**	.501**	.601**	.465**	.561**	.460**	.755**	.385**	.429**	–

Note. FG Status = First generation status; Fam. Inc.=Family income; TOI initial = Theory of Intelligence; ANX = Anxiety; ATT = Attitude; CON = Concentration; INP = Information Processing; MOT = Motivation; SFT = Self Testing; SMI = Selecting Main Ideas; STA = Study Aids; TMT = Time Management; TST = Test Taking

Appendix E:
Accuracy and bias means and standard deviations by scale

Anxiety

	Initial					Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	142	35.2	23.6	35.5	23.2	-0.1	25.9	19.7	16.7
2nd Quartile	117	24.9	24.4	28.7	19.7	-4.3	24.4	19.9	14.6
3rd Quartile	134	4.7	19.5	15.9	12.1	-3.6	22.7	16.7	15.8
Top Quartile	114	-12.8	17.3	15.8	14.6	-0.3	19.4	11.0	16.0

Attitude

	Initial					Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	180	57.7	21.3	57.7	21.1	15.2	28.8	24.8	21.0
2nd Quartile	110	54.0	19.4	54.0	19.4	12.4	29.2	25.2	19.1
3rd Quartile	94	32.0	18.1	33.4	15.2	12.7	26.1	24.5	15.3
Top Quartile	123	9.9	14.9	14.8	10.0	8.6	22.1	17.2	16.2

Concentration

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	145	35.8	19.7	35.9	19.5	2.5	24.5	19.4	15.1
2nd Quartile	125	29.8	18.9	31.0	16.7	1.5	23.0	17.1	15.3
3rd Quartile	139	16.8	16.9	20.1	12.8	-2.0	20.9	16.5	12.7
Top Quartile	98	-3.4	16.8	12.1	12.1	1.4	17.8	12.0	13.1

Information Processing

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	126	44.7	19.5	44.8	19.1	0.2	30.7	24.3	18.6
2nd Quartile	163	22.9	20.1	25.9	16.1	-6.2	23.3	19.3	14.5
3rd Quartile	129	-3.0	19.8	15.6	12.6	-5.5	18.6	14.6	12.8
Top Quartile	89	-16.6	19.3	18.4	17.6	-3.2	14.3	10.9	9.8

Motivation

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	136	42.0	20.4	42.4	19.6	6.2	28.4	22.2	18.6
2nd Quartile	117	30.2	19.5	31.1	18.1	1.6	23.4	18.2	14.6
3rd Quartile	126	7.8	20.3	18.1	12.0	1.3	22.3	17.4	13.9
Top Quartile	128	-7.6	16.8	12.4	13.6	2.0	17.6	11.6	13.4

Self Testing

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	169	41.5	21.2	41.5	21.2	-1.5	27.9	21.1	18.2
2nd Quartile	100	30.1	19.0	30.6	18.5	-4.9	30.3	24.2	18.8
3rd Quartile	114	15.3	19.3	20.4	13.8	-6.4	24.9	20.4	15.5
Top Quartile	124	-8.5	21.7	17.3	15.6	-2.0	19.3	13.7	13.7

Selecting Main Ideas

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	143	43.9	21.9	44.2	21.3	-4.5	27.2	21.0	17.8
2nd Quartile	113	28.3	22.2	31.0	18.3	-7.4	26.1	20.9	17.2
3rd Quartile	142	14.5	17.7	18.9	13.0	-7.6	19.6	16.5	13.0
Top Quartile	109	-10.2	16.0	14.2	12.5	-1.4	-14.7	10.5	10.5

Study Aids

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	132	40.5	21.6	40.8	21.0	-0.2	27.3	21.2	17.1
2nd Quartile	154	22.7	23.3	27.8	17.0	-4.3	26.9	21.5	16.2
3rd Quartile	105	2.0	18.1	14.8	10.6	-4.6	19.6	15.3	13.0
Top Quartile	116	-16.0	17.4	18.0	15.3	-1.1	14.4	10.2	10.2

Test Taking

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	149	41.8	21.5	41.9	21.3	-3.2	28.7	21.9	18.6
2nd Quartile	124	26.8	19.5	28.7	16.5	-6.9	25.7	20.9	16.3
3rd Quartile	125	5.8	19.0	16.3	11.2	-1.4	22.6	17.8	13.9
Top Quartile	109	-15.0	18.8	17.9	15.9	-1.5	12.0	9.0	8.0

Time Management

		Initial				Final			
		Signed difference (bias)		Absolute difference (accuracy)		Signed difference (bias)		Absolute difference (accuracy)	
	n	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Bottom Quartile	173	32.9	20.0	33.0	19.9	5.3	25.0	20.3	15.5
2nd Quartile	87	34.1	20.3	35.3	18.1	-0.4	22.0	17.3	13.6
3rd Quartile	140	15.9	17.7	20.1	12.8	-0.8	23.6	18.1	15.1
Top Quartile	107	-10.3	19.2	15.4	15.4	-0.6	16.0	10.5	12.1

Appendix F:
Calibration accuracy repeated measures ANOVA results

Calibration accuracy repeated measures ANOVA results: Skill factors

		F	df_1	df_{error}	p	partial η^2
Information Processing	Time	82.91	1	503	<.001	0.142
	Time * Quartile	18.81	3	503	<.001	0.101
	Quartile	83.16	3	503	<.001	0.332
Selecting Main Ideas	Time	112.22	1	503	<.001	0.182
	Time * Quartile	28.90	3	503	<.001	0.147
	Quartile	69.74	3	503	<.001	0.294
Test Taking	Time	82.06	1	503	<.001	0.140
	Time * Quartile	22.45	3	503	<.001	0.118
	Quartile	63.24	3	503	<.001	0.274

Calibration accuracy repeated measures ANOVA results: Will factors

		F	df_1	df_{error}	p	partial η^2
Anxiety	Time	46.65	1	503	<.001	0.085
	Time * Quartile	12.12	3	503	<.001	0.067
	Quartile	37.67	3	503	<.001	0.183
Attitude	Time	202.22	1	503	<.001	0.305
	Time * Quartile	58.74	3	503	<.001	0.259
	Quartile	107.91	3	503	<.001	0.392
Motivation	Time	79.74	1	503	<.001	0.137
	Time * Quartile	25.39	3	503	<.001	0.132
	Quartile	77.85	3	503	<.001	0.317

Calibration accuracy repeated measures ANOVA results: Self-regulation factors

		F	df_1	df_{error}	p	partial η^2
Concentration	Time	80.83	1	503	<.001	0.138
	Time * Quartile	17.33	3	503	<.001	0.094
	Quartile	47.50	3	503	<.001	0.221
Self Testing	Time	50.69	1	503	<.001	0.092
	Time * Quartile	21.21	3	503	<.001	0.112
	Quartile	43.21	3	503	<.001	0.205
Study Aids	Time	69.52	1	503	<.001	0.122
	Time * Quartile	17.13	3	503	<.001	0.093
	Quartile	65.66	3	503	<.001	0.282
Time Management	Time	88.63	1	503	<.001	0.150
	Time * Quartile	12.86	3	503	<.001	0.071
	Quartile	38.99	3	503	<.001	0.189

Appendix G:
T-test comparisons for Anxiety accuracy

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Bottom Quartile	142	35.5	23.2	7.92	0.000
	Top Quartile	114	15.8	14.6		
Final Anxiety Accuracy	Bottom Quartile	142	19.7	16.7	4.23	0.000
	Top Quartile	114	11.0	16.0		

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Bottom Quartile	142	35.5	23.2	2.50	.013
	Second	117	28.7	19.7		
Final Anxiety Accuracy	Bottom Quartile	142	19.7	16.7	-0.09	.928
	Second	117	19.9	14.6		

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Bottom Quartile	142	35.5	23.2	8.88	0.000
	Third	134	15.9	12.1		
Final Anxiety Accuracy	Bottom Quartile	142	19.7	16.7	1.563	0.119
	Third	134	16.7	15.7		

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Third	134	15.9	12.1	0.070	0.994
	Top Quartile	114	15.8	14.6		
Final Anxiety Accuracy	Third	134	16.7	15.7	2.802	0.005
	Top Quartile	114	11.0	16.0		

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Second	117	28.7	19.7	5.68	0.000
	Top Quartile	114	15.8	14.6		
Final Anxiety Accuracy	Second	117	19.9	14.6	4.41	0.000
	Top Quartile	114	11.0	16.0		

T-test comparing initial and final calibration accuracy

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Accuracy	Second	117	28.7	19.7	6.31	0.000
	Third	134	15.9	12.1		
Final Anxiety Accuracy	Second	117	19.9	14.6	1.69	0.09
	Third	134	16.7	15.7		

Appendix H:
Calibration bias repeated measures ANOVA results

Calibration bias repeated measures ANOVA results: Skill factors

		F	df_1	df_{error}	p	partial η^2
Information Processing	Time	141.09	1	503	<.001	0.219
	Time * Quartile	90.03	3	503	<.001	0.349
	Quartile	93.88	3	503	<.001	0.359
Selecting Main Ideas	Time	398.12	1	503	<.001	0.442
	Time * Quartile	96.97	3	503	<.001	0.366
	Quartile	55.45	3	503	<.001	0.249
Test Taking	Time	180.79	1	503	<.001	0.264
	Time * Quartile	95.40	3	503	<.001	0.363
	Quartile	69.07	3	503	<.001	0.292

Calibration bias repeated measures ANOVA results: Will factors

		F	df_1	df_{error}	p	partial η^2
Anxiety	Time	121.47	1	503	<.001	0.195
	Time * Quartile	61.41	3	503	<.001	0.268
	Quartile	53.54	3	503	<.001	0.242
Attitude	Time	300.64	1	503	<.001	0.374
	Time * Quartile	46.76	3	503	<.001	0.218
	Quartile	76.02	3	503	<.001	0.312
Motivation	Time	135.72	1	503	<.001	0.212
	Time * Quartile	63.82	3	503	<.001	0.276
	Quartile	77.66	3	503	<.001	0.317

Calibration bias repeated measures ANOVA results: Self-regulation factors

		F	df_1	df_{error}	p	partial η^2
Concentration	Time	235.17	1	503	<.001	0.319
	Time * Quartile	41.99	3	503	<.001	0.200
	Quartile	43.05	3	503	<.001	0.204
Self Testing	Time	288.70	1	503	<.001	0.365
	Time * Quartile	68.45	3	503	<.001	0.290
	Quartile	51.86	3	503	<.001	0.236
Study Aids	Time	123.16	1	503	<.001	0.197
	Time * Quartile	82.20	3	503	<.001	0.329
	Quartile	74.79	3	503	<.001	0.308
Time Management	Time	171.55	1	503	<.001	0.254
	Time * Quartile	49.21	3	503	<.001	0.227
	Quartile	63.90	3	503	<.001	0.276

Appendix I:
T-test comparisons for Anxiety bias

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Bottom Quartile	142	35.2	23.6	18.75	0.000
	Top Quartile	114	-12.8	17.3		
Final Anxiety Bias	Bottom Quartile	142	-0.11	25.9	0.072	0.945
	Top Quartile	114	-0.32	19.4		

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Bottom Quartile	142	35.2	23.6	3.449	0.001
	Second	117	24.9	24.4		
Final Anxiety Bias	Bottom Quartile	142	-0.11	25.9	1.322	0.187
	Second	117	-4.3	24.4		

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Bottom Quartile	142	35.2	23.6	11.75	0.000
	Third	134	4.7	19.5		
Final Anxiety Bias	Bottom Quartile	142	-0.11	25.9	1.194	0.234
	Third	134	-3.6	22.7		

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Third	134	4.7	19.5	7.401	0.000
	Top Quartile	114	-12.8	17.3		
Final Anxiety Bias	Third	134	-3.6	22.7	-1.23	0.220
	Top Quartile	114	-0.32	19.4		

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Second	117	24.9	24.4	13.49	0.000
	Top Quartile	114	-12.8	17.3		
Final Anxiety Bias	Second	117	-4.3	24.4	-1.36	0.175
	Top Quartile	114	-0.32	19.4		

T-test comparing initial and final calibration bias

		n	*M*	*SD*	*t*	*Sig. (2-tailed)*
Initial Anxiety Bias	Second	117	24.9	24.4	7.179	0.000
	Third	134	4.7	19.5		
Final Anxiety Bias	Second	117	-4.3	24.4	-.225	0.822
	Third	134	-3.6	22.7		

Appendix J:
Overall regression analyses

*Regression Examining **Initial Anxiety** Actual Score*

Model		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	3.36			
	Prediction	0.06	.558***	.311	
2	(Constant)	4.49			.041***
	Prediction	0.06	.547***	.353	
	Generation Status	3.25	.110*		
	Income	3.27	.039		
	Ethnicity	3.09	-.116*		
3	(Constant)	5.64		.353	.000
	Prediction	0.06	.551***		
	Generation Status	3.25	.110*		
	Income	3.27	.039		
	Ethnicity	3.10	-.117*		
	Theory of Intelligence	1.32	.003		

Note. *$p < .05$. **$p < .01$. ***$p \le .001$.

*Regression Examining **Final Anxiety** Actual Score*

Model		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	3.11			
	Prediction	0.05	.628***	.393	
2	(Constant)	4.12			.003
	Prediction	0.05	.631***	.390	
	Generation Status	2.78	.035		
	Income	2.79	-.056		
	Ethnicity	2.65	-.023		
3	(Constant)	5.02		.389	.000
	Prediction	0.05	.630***		
	Generation Status	2.79	.035		
	Income	2.79	-.055		
	Ethnicity	2.66	-.023		
	Theory of Intelligence	1.14	.010		

Note. *$p < .05$. **$p < .01$. ***$p \le .001$.

*Regression Examining **Initial Attitude** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	4.76			
	Prediction	0.06	.432***	.186	
2	(Constant)	5.72			.015
	Prediction	0.06	.437***	.202	
	Generation Status	3.02	.083		
	Income	3.01	-.102		
	Ethnicity	2.88	-.088		
3	(Constant)	6.06		.264	.063***
	Prediction	0.06	.396***		
	Generation Status	2.91	.079		
	Income	2.90	-.092		
	Ethnicity	2.77	-.105*		
	Theory of Intelligence	1.19	.254***		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Final Attitude** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.78			
	Prediction	0.06	.503***	.251	
2	(Constant)	5.00			.006
	Prediction	0.06	.507***	.250	
	Generation Status	3.17	.016		
	Income	3.16	-.063		
	Ethnicity	3.02	-.068		
3	(Constant)	5.69		.264	.015**
	Prediction	0.06	.483***		
	Generation Status	3.14	.014		
	Income	3.13	-.057		
	Ethnicity	2.99	-.075		
	Theory of Intelligence	1.30	.016**		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Initial Concentration** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.31			
	Prediction	0.06	.599***	.359	
2	(Constant)	4.26			.009
	Prediction	0.06	.599***	.367	
	Generation Status	2.73	.042		
	Income	2.73	-.038		
	Ethnicity	2.59	-.083		
3	(Constant)	5.01		.374	.006
	Prediction	0.06	.589***		
	Generation Status	2.71	.041		
	Income	2.72	-.034		
	Ethnicity	2.59	-.089		
	Theory of Intelligence	1.11	.081		

Note. **p* < .05. ***p* < .01. ****p* ≤ .001.

*Regression Examining **Final Concentration** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.05			
	Prediction	0.05	.632***	.400	
2	(Constant)	3.94			.005
	Prediction	0.05	.632***	.405	
	Generation Status	2.52	.007		
	Income	2.51	-.072		
	Ethnicity	2.40	-.004		
3	(Constant)	4.65		.405	.001
	Prediction	0.05	.629***		
	Generation Status	2.52	.007		
	Income	2.51	-.071		
	Ethnicity	2.40	-.005		
	Theory of Intelligence	1.03	.027		

Note. **p* < .05. ***p* < .01. ****p* ≤ .001.

Regression Examining ***Initial Information Processing*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	4.79			
	Prediction	0.08	.360***	.130	
2	(Constant)	5.75			.051***
	Prediction	0.08	.364***	.181	
	Generation Status	3.38	.151**		
	Income	3.41	-.165**		
	Ethnicity	3.22	-.168***		
3	(Constant)	6.59		.182	.001
	Prediction	0.08	.360***		
	Generation Status	3.38	.151**		
	Income	3.42	-.163**		
	Ethnicity	3.23	-.170***		
	Theory of Intelligence	1.39	.030		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

Regression Examining ***Final Information Processing*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	3.67			
	Prediction	0.05	.524***	.274	
2	(Constant)	4.56			.005
	Prediction	0.05	.519***	.280	
	Generation Status	2.67	.041		
	Income	2.66	-.026		
	Ethnicity	2.54	-.061		
3	(Constant)	5.24		.280	.000
	Prediction	0.05	.519***		
	Generation Status	2.67	.041		
	Income	2.67	-.026		
	Ethnicity	2.55	-.061		
	Theory of Intelligence	1.09	.001		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

Regression Examining ***Initial Motivation*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	4.57			
	Prediction	0.07	.503***	.253	
2	(Constant)	5.62			.043***
	Prediction	0.06	.504***	.296	
	Generation Status	3.23	.166***		
	Income	3.22	-.014		
	Ethnicity	3.08	-.094		
3	(Constant)	6.33		.313	.017**
	Prediction	0.06	.486***		
	Generation Status	3.20	.165***		
	Income	3.19	-.010		
	Ethnicity	3.06	-.104*		
	Theory of Intelligence	1.31	.131**		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

Regression Examining ***Final Motivation*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.61			
	Prediction	0.05	.611***	.373	
2	(Constant)	4.45			.002
	Prediction	0.05	.611***	.375	
	Generation Status	2.73	-.004		
	Income	2.72	.002		
	Ethnicity	2.60	-.041		
3	(Constant)	5.02		.389	.014**
	Prediction	0.05	.587***		
	Generation Status	2.70	-.002		
	Income	2.69	.006		
	Ethnicity	2.57	-.049		
	Theory of Intelligence	1.12	.122**		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Initial Selecting Main Ideas** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	4.31			
	Prediction	0.07	.458***	.209	
2	(Constant)	5.21			.016
	Prediction	0.07	.434***	.225	
	Generation Status	3.15	.033		
	Income	3.20	.056		
	Ethnicity	3.00	-.079		
3	(Constant)	6.02		.231	.006
	Prediction	0.70	.424***		
	Generation Status	3.14	.032		
	Income	3.20	-.061		
	Ethnicity	3.00	-.084		
	Theory of Intelligence	1.29	.075		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Final Selecting Main Ideas** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.12			
	Prediction	0.05	.554***	.307	
2	(Constant)	3.86			.004
	Prediction	0.05	.561***	.311	
	Generation Status	2.34	-.032		
	Income	2.36	-.051		
	Ethnicity	2.25	-.015		
3	(Constant)	4.53		.311	.000
	Prediction	0.05	.560***		
	Generation Status	2.36	-.032		
	Income	2.36	-.051		
	Ethnicity	2.25	-.016		
	Theory of Intelligence	0.96	.008		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Initial Self Testing** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.66			
	Prediction	0.06	.403***	.162	
2	(Constant)	4.71			.023*
	Prediction	0.06	.391***	.185	
	Generation Status	3.13	.102		
	Income	3.13	-.080		
	Ethnicity	3.00	-.115*		
3	(Constant)	5.65		.189	.003
	Prediction	0.06	.384***		
	Generation Status	3.13	.102		
	Income	3.13	-.077		
	Ethnicity	3.00	-.120*		
	Theory of Intelligence	1.28	.059		

Note. $*p < .05$. $**p < .01$. $***p \leq .001$.

*Regression Examining **Final Self Testing** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.40			
	Prediction	0.05	.525***	.275	
2	(Constant)	4.58			.005
	Prediction	0.05	.525***	.280	
	Generation Status	2.03	.023		
	Income	3.01	-.079		
	Ethnicity	2.88	-.010		
3	(Constant)	5.52		.280	.000
	Prediction	0.05	.525***		
	Generation Status	3.03	.023		
	Income	3.02	-.609		
	Ethnicity	2.89	-.010		
	Theory of Intelligence	1.23	-.006		

Note. $*p < .05$. $**p < .01$. $***p \leq .001$.

Regression Examining ***Initial Study Aids*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	4.41			
	Prediction	0.07	.414***	.172	
2	(Constant)	5.47			.021*
	Prediction	0.07	.410***	.192	
	Generation Status	3.43	.158**		
	Income	3.43	-.08		
	Ethnicity	3.26	-.015		
3	(Constant)	6.31		.209	.016**
	Prediction	0.07	.390***		
	Generation Status	3.40	.158**		
	Income	3.40	-.077		
	Ethnicity	3.24	-.024		
	Theory of Intelligence	1.39	.130**		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

Regression Examining ***Final Study Aids*** *Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.26			
	Prediction	0.05	.603***	.363	
2	(Constant)	4.22			.012
	Prediction	0.05	.600***	.375	
	Generation Status	2.62	.119*		
	Income	2.62	-.018		
	Ethnicity	2.50	-.038		
3	(Constant)	4.87		.378	.002
	Prediction	0.05	.591***		
	Generation Status	2.62	.120*		
	Income	2.62	-.016		
	Ethnicity	2.50	-.035		
	Theory of Intelligence	1.08	.050		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Initial Test Taking** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	4.36			
	Prediction	0.07	.381***	.145	
2	(Constant)	5.42			.055***
	Prediction	0.07	.339***	.200	
	Generation Status	3.29	.037		
	Income	3.30	.120*		
	Ethnicity	3.15	-.147**		
3	(Constant)	6.29		.211	.011*
	Prediction	0.07	.328***		
	Generation Status	3.27	.037		
	Income	3.29	.125*		
	Ethnicity	3.14	-.155**		
	Theory of Intelligence	1.34	.106*		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Final Test Taking** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	β	R^2	ΔR^2
1	(Constant)	3.52			
	Prediction	0.02	.471***	.222	
2	(Constant)	4.39			.007
	Prediction	0.05	.472***	.228	
	Generation Status	2.63	-.003		
	Income	2.63	-.069		
	Ethnicity	2.51	-.071		
3	(Constant)	5.08		.240	.011*
	Prediction	0.05	.461***		
	Generation Status	2.62	-.003		
	Income	2.62	-.064		
	Ethnicity	2.50	-.079		
	Theory of Intelligence	1.07	.108*		

Note. *$p < .05$. **$p < .01$. ***$p \leq .001$.

*Regression Examining **Initial Time Management** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	3.50			
	Prediction	0.06	.533***	.284	
2	(Constant)	4.76			.009
	Prediction	0.06	.530***	.293	
	Generation Status	3.17	.107*		
	Income	3.16	-.055		
	Ethnicity	3.02	-.009		
3	(Constant)	5.56		.299	.006
	Prediction	0.06	.514***		
	Generation Status	3.16	.107*		
	Income	3.15	-.052		
	Ethnicity	3.02	-.015		
	Theory of Intelligence	1.31	.077		

Note. * $p < .05$. ** $p < .01$. *** $p \leq .001$.

*Regression Examining **Final Time Management** Actual Score*

Step		Standardized Coeff		Change Statistics	
		Std. Error	*β*	R^2	ΔR^2
1	(Constant)	2.97			
	Prediction	0.05	.650***	.422	
2	(Constant)	3.97			.013*
	Prediction	0.05	.654***	.435	
	Generation Status	2.63	.061		
	Income	2.63	-.131**		
	Ethnicity	2.51	-.034		
3	(Constant)	4.68		.435	.000
	Prediction	0.05	.651***		
	Generation Status	2.64	.061		
	Income	2.63	-.131**		
	Ethnicity	2.51	-.035		
	Theory of Intelligence	1.09	.017		

Note. * $p < .05$. ** $p < .01$. *** $p \leq .001$.

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